THREE ESSAYS ON BUSINESS FAILURE:

CAUSALITY AND PREDICTION

A Dissertation

by

JIN ZHANG

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2006

Major Subject: Agricultural Economics

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Approved by:

Chair of Committee, David J. Leatham
Committee Members, David A. Bessler
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ABSTRACT

Three Essays on Business Failure: Causality and Prediction.

(December 2006)

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This dissertation investigates three issues on business failure causality and prediction. First, a nonlinear model for mathematical programming based discriminant analysis is studied. This study proposes a nonlinear model that builds on the existing linear and quadratic models and allows for a more flexible degree of nonlinearity through a set of power parameters. The proposed nonlinear model is solved using a genetic algorithm and is tested against linear and quadratic models using real financial data. The results show that each model is better in certain cases, but the nonlinear model turns out to be the best overall among the three. Better performance of this nonlinear model appears likely, but a more robust solver would be required.

Second, the relationship between aggregate business failures and macroeconomic conditions is studied from a causality perspective. A structural Vector Autoregression (VAR) is used while incorporating the recently developed causal inference method Directed Acyclic Graph (DAG). Particularly, DAG is used to provide a contemporaneous causal structure and the VAR results are summarized using innovation accounting techniques. The results show that during the period from 1980 to 2004 in the U.S., aggregate business failures were influenced by interest rates, but overall these failures appear to be far more exogenous than was found previously.

Third, the effect of incorporating macroeconomic variables into business failure prediction models is investigated with a focus on the U.S. airline industry from 1995 to 2005. The attention is placed on prediction accuracy, parameter stability, and the effect of particular macroeconomic variables. The results show that the stability of parameters in the prediction model is improved when macro variables are added. In terms of prediction accuracy, the model augmented with a macro variable performed better in a jackknife prediction, but not in out-of-sample predictions. The macroeconomic variable found to be significant is the change of interest rate, which is probably related to the high level of leverage common in this particular industry. Also, the results demonstrate that a probability score can be used as a more informative evaluation measure than the current one based on cutoff probabilities.

DEDICATION

To my grandparents, my mom and dad, and my wife

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CHAPTER I

INTRODUCTION

The academic discipline has been predicting business failure (or bankruptcy, interchangeably henceforward) for decades, especially following the pioneering work by Beaver (1966) and Altman (1968). The prediction of business failure has been interesting because there are usually huge costs associated a bankruptcy, and that impacts all parties involved: the owners or shareholders, management, lenders, the government, even the general public. The research of business failure prediction has been mostly empirical and higher prediction accuracy is the main objective of all studies. Towards this objective, the use of statistical/mathematical model, and the choice of independent variables are the two basic factors critical to any business failure prediction.

This dissertation investigates three issues related to the business failure prediction. Specifically, the three issues studied are as follows. The first issue studies whether a nonlinear formulation for mathematical programming based discriminant analysis is more effective than existing linear and quadratic formulations. The second issue studies the causality relationship between aggregate business failures and macroeconomic conditions. The third issue studies the effect of macroeconomic variables in failure prediction model by examining the case of US airline industry. The first and third issues contribute directly to the two aspects of failure prediction: the development of statistical model, and the choice of independent variables. The second

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This dissertation follows the format of *Applied Economics*.

issue is a macro one and its role is two fold. First, at the macro level, the causality associated aggregate business failures has macro policy implications; second, the causing factors identified at the macro level is expected to provide guidance for the choice of independent variables in firm level failure prediction, covered in the third issue.

Statistical/mathematical method in business failure prediction was introduced by Altman (1968), following immediately the univariate analysis of Beaver (1966). Altman proposed the use of Discriminant Analysis[1] (DA) to enable a combined analysis of multiple variables. Discriminant analysis model is essentially the model called Fisher (1936) linear discriminant function (LDF) elsewhere. In the 1980s, Logit (Ohlson, 1980), Probit (Zmijewski, 1984) entered the literature as a second generation statistical model for business failure prediction. In the above methods, an underlying distribution of data is assumed and for this reason they have been classified as parametric models.

Parallel to the development of parametric methods is that of nonparametric methods. Particularly, since the early 1980s, Mathematical Programming (MP) as an important nonparametric method has been introduced as a tool of classification, and has been used in such applications as credit scoring as well as business failure prediction. Across all existing MP formulations, the constraint functions have all been linear, except the quadratic formulation proposed by Silva and Stam (1994). The quadratic formulation represents an improvement over linear MP in certain cases. This

[1] Outside business failure prediction literature, discriminant analysis has a more general meaning that essentially means classification. We take the general definition when it is used in Chapter II.

formulation, however, is still restrictive in functional form and in practice requires a preparation of quadratic terms by its users. As the constraint functions of MP serve as a hyperplane that separates two (or multiple) groups, a more general nonlinear hyperplane would be more flexible and is expected to lead to better classification performance. We propose such a nonlinear separation function, solve the resulting nonlinear optimization problem using global optimizer Genetic Algorithm, and test its performance based on real financial data on credit scoring and bank ranking. This is the first issue studied in this dissertation.

The choice of independent variables is the second basic issue for business failure prediction. From the very start, firm specific financial data has been the primary source of information for prediction analysis. This line of research was represented first by ratio analysis using single financial ratio (Beaver, 1966), and later, by methods incorporating multiple financial variables (Altman, 1968). Firm level information usually comes from firm financial ratios, the so-called accounting based data. In addition, firm specific information comes from markets, e.g., stock price of a company. Beyond firm level variables, the failures of firms are also subject to factors external to a firm. Industry effect is one such factor (Altman and Izan (1984), Izan (1984), Platt and Platt (1990, 1991), Chava and Jarrow (2004)).

Macroeconomic environment represents another factor external to firm. Economic intuitions tend to suggest that the occurrence of business failures is influenced by macroeconomic conditions. Empirical study of this issue has been conducted at the macro level mostly from a time series perspective. Based on an analysis of financially vulnerable firms, Altman (1971, 1983) suggested business failure rates may be determined by real economic growth, credit or money market activity, capital market activity, business population characteristics, and inflation. The regression results verified the existence of the associations between aggregate business failure rates and some of the above macroeconomic variables. Rose et al. (1982) started with a wide spectrum of macroeconomic indicators and reduced them into a compact set of 6 variables via statistical analysis: the SP500 index, the prime rate, the 90-day treasury bill rate, and three non-monetary supply and demand factors. Melicher and Hearth (1988) focused on only particular aspect of macro economy and proposed aggregate business failures as a function of financial markets. Drawing on the shutting down condition in neoclassic microeconomic theory, Platt and Platt (1994) assumed aggregate corporate failure as a function of general cost and economic conditions (revenue benchmark). Across all the differing frameworks, the empirical literature seems to approach a consensus regarding certain variables, including corporate profits, and interest rate. Little consensus or conflicting results exist regarding the other variables, particularly inflation, and stock market performance.

At the micro level, the use of macroeconomic conditions as independent variables in failure prediction is more recent. Mensah (1984) cautioned against the impact of change of macroeconomic environment on the performance of business failure prediction. Further, Kane et al. (1996) and Richardson et al. (1998) evaluated the impact of recession on failure prediction. Studies incorporating general macroeconomic conditions began to emerge since the 1ate 1990s. A partial list of them includes those by Lennox (1999), Tirapat and Nittayagasetwat (1999), Duffie and Wang (2004), and Hunter and Isachenkova (2006). Macroeconomic indicators, including business confidence index, economic growth, inflation, interest rates, personal income growth, exchange rate, or their changes, are the variables covered in the above failure prediction models. Among them, Hunter and Isachenkova (2006) differ from the others in the comparative approach they take in evaluating the incremental effect of macro variables on failure prediction.

Given the current literature, the influences of macroeconomic conditions on aggregate business failures and their impact on business failure prediction are studied respectively as the second and third issue in this dissertation. First, at the macro level, the relationship between aggregate business failures and macroeconomic conditions is investigated. The motivation for such a study is first the existing conflicting findings regarding certain macroeconomic variables, as mentioned above. A further motivation is to distinguish more carefully between the association and causation and thus reveal the business failure-macro economy relationship in a causal perspective. This is enabled by an approach that combines structural vector autoregression (VAR) and directed acyclic graphs (DAG). The essence of this approach is to rely on DAG to provide a "data-driven" causal structure and input it into structural VAR to reveal the relationship between variables involved (Swanson and Granger, 1997; Bessler and Yang, 2003). This is the second issue we study in this dissertation.

Second, at the micro level, we investigate the use of macroeconomic conditions as independent variables in business failure prediction. Despite a growing presence of macro variables in failure prediction, few studies have evaluated their effect on prediction accuracy in a comparative manner, which leaves the real effect of macro variables on business failure prediction unanswered. An answer to this question is necessary because firm financial ratios are subject to the influence of macro economic conditions and they are already part of the prediction model. What the macro variables can add incrementally is another question and should be subject to empirical testing. Based on this motivation, we evaluate the use of macroeconomic conditions as independent variables in failure prediction model. Beside an evaluation on the improvement of prediction accuracy, parameter stability, the effect of particular macroeconomic variables are also studied in a single industry context. This is the third issue we study in this dissertation.

In the remainder of this dissertation, the above three issues are investigated by three essays, covered in Chapter II, III, and IV respectively. Each of the three chapters is self-contained and follows a journal article style. Following the three chapters, Chapter V concludes the dissertation with a summary of the three essays.

CHAPTER II

A NONLINEAR MODEL FOR MATHEMATICAL PROGRAMMING BASED DISCRIMINANT ANALYSIS

2.1 Introduction

Since its introduction into Discriminant Analysis (DA) in the early 1980s, Mathematical Programming (MP) has been much studied as an important nonparametric DA technique. Compared to parametric models in DA, nonparametric MP methods do not depend on the restrictive assumptions of underlying distribution. Since violation of statistical distributions is more likely the rule than the exception (Eisenbeis, 1977), MP based DA models have been found by some studies to be more appropriate and consequently more effective than parametric ones. MP based DA models have been commonly used in decision science. Some notable applications are in the finance field, specifically financial distress prediction and credit granting (Dimitras et al, 1996; Thomas, 2000; Ziari et al, 1995).

As defined by their objective function, different MP based DA models have been developed, the Minimize the Sum of Deviations (MSD) (Hand, 1981; Freed and Glover, 1981b), the Minimize the Maximum Deviation (MMD) (Freed and Glover, 1981a), the Minimize the Number of Misclassifications via Mixed Integer Programming (MIP) (Bajgier and Hill, 1982), are among the most commonly used. In the meantime, despite these multiple models and their extensive applications, all of them are based on linear classification functions. Linear classification functions are easier to solve, but they are also restrictive and not always the most suitable model in all situations. In 1994, Silva and Stam introduced quadratic terms into classification functions and found the resulting quadratic models outperformed linear ones where appropriate[2].

This study seeks to take this concept of nonlinear classification function one step further. The quadratic model provides a desirable nonlinear alternative to the common linear models, but it is not without limitations. Most notably, the quadratic formulation is effective only in certain conditions and will fail to perform as well where it is not applicable. In this study, instead of proposing a formulation of a higher order to meet complex data conditions, we propose a nonlinear MP based DA model designed to adjust to varying data situations. The essence of this model is a more generalized nonlinear classification function (constraint function) in which an additional set of power parameters can be optimized to minimize the objective function and thus improve classification performance. The objective functions in the model are application specific and are not changed by the classification function.

Given the conceptual formulation, how to solve this nonlinear MP problem is itself a challenge. With the introduction of nonlinear terms in the classification (constraint) functions, the MP based DA setup as an optimization problem will be hard to solve, much less guarantee global optimality[3]. For this reason, we seek a robust optimization algorithm and genetic algorithm (GA) is selected for its cited capability to

[2] According to Silva and Stam (1994), one case in which quadratic function is preferred to linear one is when the variance-covariance is obviously heterogeneous across two groups. One the other hand, they suggested that quadratic function is inferior to linear one when the attributes are not correlated.

[3] This is not a problem in Silva and Stam second order model. Quadratic terms of attributes are preprocessed and this resulting DA problem is linear in nature and can be solved easily.

converge to global optima regardless of function irregularity. Our best hope is that this optimizer will reach global optimality for the proposed nonlinear model; at the minimum, we expect to see the proposed model be solved as completely as possible.

In short, this study tests an MP based DA model based on a nonlinear classification function. The GA as a robust optimization algorithm is used to solve the proposed model. In the rest of this chapter, section 2.2 reviews two important MP based DA models; Section 2.3 introduces the proposed nonlinear formulation; Section 2.4 describes the genetic algorithm; Section 2.5 evaluates the model empirically; and section 2.6 concludes the chapter.

2.2 Mathematical Programming for Discriminant Analysis

DA usually consists of two steps. First, the classification rule(s) are established using training samples in which the group membership of observations are known. Second, the established classification rules are subsequently used to predict membership for future observations whose membership is not known. When MP is used for DA, constraint functions work as hyperplane that separates different (usually two) groups of observations, the observations are classified into one of the predefined groups depending on if they satisfy or violate the constraints. Therefore, in MP based DA, the process of establishing the classification function is about the definition of the constraint function.

We review below in greater detail two types of MP based DA models: MSD and MIP. Both models differ in their objective function, but they both build on the same type of linear constraint functions. In this study, these two models are chosen to be the base of the proposed model and will be evaluated later for the purpose of model comparison.

The first one is MSD (Freed and Glover, 1981b; Hand, 1981). MSD may be the most commonly studied and was cited as one of the two most successful MP formulations for analyzing the discriminant problem (Duarte Silva and Stam, 1994). For a two-group discriminant problem, suppose a training sample with ($n_1 + n_2$) observations, where n_1 and n_2 are the number of observations belonging to group 1 and group 2 respectively. Each observation in this sample is described by k variables (attributes). For the classification of such a problem, the MSD model can be expressed as follows.

$$\underset{w_j, c}{Minimize} \sum_{i \in G_1} d_{i1}^{+} + \sum_{i \in G_2} d_{i2}^{-} \tag{2.1}$$

subject to

$$\sum_j w_j a_{ij} - d_{i1}^{+} + d_{i1}^{-} \le c, \; i = 1, \dots, n_1 \;\; \text{(Group1)} \tag{2.2}$$

$$\sum_j w_j a_{ij} - d_{i2}^{+} + d_{i2}^{-} > c, \; i = 1, \dots, n_2 \;\; \text{(Group2)} \tag{2.3}$$

$$d_{ir}^{+}, d_{ir}^{-} \ge 0, \; i = 1, \dots, n_r, \; r = 1,2, \tag{2.4}$$

$$w_j, c \text{ unrestricted}, \; j = 1, \cdots, k \tag{2.5}$$

where the a_{ij} represents the j_{th} attribute value for the i_{th} observation. The d_{ir}^{+} and d_{ir}^{-} ($i = 1, \dots, n_r$, $r = 1,2$) measure external or internal deviations from the separating hyperplane. w_j is the weight coefficient associated with the j_{th} attribute while c is the cut-off value. w_j and c are the variables to be optimized and will define the resulting classification function.

For a specific observation, unless it is exactly on the separating hyperplane, either internal or external deviation, d_{ir}^{+} or d_{ir}^{-}, not both, will happen. Internal deviation means an observation is correctly classified and deviating away from the hyperplane. Therefore, the greater the internal deviation, the better the classification performance. The opposite is true of external deviation. The objective in MSD is to minimize the sum of all the external deviations d_{i1}^{+} and d_{i2}^{-}. The MSD model was originally reported by Freed and Glover (1981b) without a normalization constraint. Later they included a normalization constraint (Freed and Glover, 1986) to overcome the difficulties associated with unacceptable solutions.

The second model evaluated is MIP. For the aforementioned problem of ($n_1 + n_2$) observations described by k attributes, the MIP formulation can be expressed as follows:

$$\underset{w_j, c}{Minimize} \sum_{i \in G_1} Y(d_{i1}^{+}) + \sum_{i \in G_2} Y(d_{i2}^{-}) \tag{2.6}$$

subject to

$$\sum_j w_j a_{ij} - d_{i1}^{+} + d_{i1}^{-} \le c, \; i = 1, ..., n_1 \;\; \text{(Group1)} \tag{2.7}$$

$$\sum_j w_j a_{ij} - d_{i2}^{+} + d_{i2}^{-} > c, \; i = 1, ..., n_2 \;\; \text{(Group2)} \tag{2.8}$$

$$d_{ir}^{+}, d_{ir}^{-} \ge 0, \; i = 1, ..., n_r, \; r = 1, 2, \tag{2.9}$$

$$w_j, c \;\text{ unrestricted}, \; j = 1, \cdots, k \tag{2.10}$$

where all the parameters are as defined in MSD, except that Y is a binary variable that equals one if individual i is misclassified, i.e., d_{i1}^{+} or d_{i2}^{-} occurs, and zero otherwise.

MIP is chosen because it is the only model that directly minimizes the number of misclassifications. Although minimizing the number/percentage of misclassification is the ultimate[4] objective of discriminant analysis and with little exception is also the measure by which different models are evaluated, all MP based DA models except MIP actually approach this objective indirectly. That is, those models seek to minimize a proxy that is highly correlated with this ultimate objective. As shown above, in MSD the sum of deviations d_{i1}^{+} and d_{i2}^{-} is such a proxy. In the MIP model, however, the number/percentage of misclassifications is presented as the objective function directly. When computational capability is not a problem, this direct expression of objective function in MIP should make it easier to reach the highest possible classification performance, therefore making MIP preferred over other models.

Beside the resulting higher classification performance, the direct attack on the number of misclassifications makes it easy to incorporate cost considerations into the discriminant analysis. This is especially necessary when misclassification costs for both groups are not equal. For example, the cost of rejecting a profitable loan application or granting a loan that defaults is definitely different to a lending institution. The incorporation of misclassification costs is not the focus of this study, but MIP's ability to do so will be accounted for through unequal weights for misclassification of each group.

In short, like other MP formulations, MSD and MIP differ in their objective functions, but both models rely on linear constraint functions to separate observations belonging to different groups. While computationally easy, this formulation is not flexible in general and can limit the performance of classification.

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[4] This word is used in a relative sense. The number of misclassification is not necessarily the most important objective. This is particularly true when the cost of misclassifying for either group is not the same weight.

2.3 The Nonlinear Formulation

Silva and Stam (1994) argued through a two-attribute DA problem, a quadratic function F_Q will have the potential of yielding a satisfactory classification where a linear function F_l is incapable of correctly separating the two groups of observations when the variance-covariance is strongly heterogeneous across groups. They proposed a second order MP formulation in which the classification functions contain linear terms of attributes; quadratic and cross-product terms of the original attributes will also be created and included in the classification function if preliminary analysis of data indicates the desirability to do so. These quadratic terms, along with the original linear terms, are then subject to the usual optimization procedure to find the linear discriminant function; this procedure can be implemented on any standard linear MP package. In addition to the test of this model by simulation data by Silva and Stam, Banks and Abad (1994) also used real world research data sets in the literature to test this quadratic transformation approach and found that this method outperformed Quadratic Discriminant analysis (QDF).

The second order MP formulation represents significant progress in the MP models' adaptability when applied to DA. However, the second order formulation approach should only be applied where appropriate and requires a preliminary analysis of the data sets. It still lacks flexibility in more general data situations.

Beyond the second order model by Silva and Stam, we propose a more general type of nonlinear MP formulation for DA. The main feature of this nonlinear model is, in addition to the linear coefficients, a set of parameters that allow varying degrees of nonlinearity in the classification function. This classification function F_i is as follows:

$$F_i = X_0 + X_1 \cdot sign(B_{i1}) \cdot | B_{i1} |^{Y1} + ... + X_J \cdot sign(B_{iJ}) \cdot | B_{iJ} |^{YJ} ,$$

where B_{ij} s correspond to the attributes (a_{ij} s) in DA, X_j s are the same set of linear coefficients (weight) as in the linear MP models (w_j). Y_j is the set of parameters that are introduced to capture nonlinearity. Ideally, Y_j takes any reasonable value to adapt to a given data situation. For example, when $Y_j > 2$, this classification function represents a nonlinear separating hyperplane; when $Y_j = 1$, it becomes the common linear function form. Given the possible negative and zero values for attributes, Y_j is restricted to be positive and the absolute value of B_{ij} is used for nonlinear transformation.

This classification function can be incorporated into different MP based DA models. The MSD and MIP models based on this nonlinear classification function take the form as below.

$$\underset{w_j, z_j, c}{Minimize} \sum_{i \in G_1} d_{i1}^{+} + \sum_{i \in G_2} d_{i2}^{-} \tag{2.11}$$

subject to $\sum_j w_j \cdot sign(a_{ij}) \cdot | a_{ij} |^{z_j} - d_{i1}^{+} + d_{i1}^{-} \le c$, $i = 1,..., n_1$ (Group1) (2.12)

$$\sum_j w_j \cdot sign(a_{ij}) \cdot | a_{ij} |^{z_j} - d_{i2}^{+} + d_{i2}^{-} > c \,,\; i = 1,..., n_2 \text{ (Group2)} \tag{2.13}$$

$$d_{ir}^{+}, d_{ir}^{-} \ge 0 \,,\; i = 1,..., n_r \,,\; r = 1,2 \,, \tag{2.14}$$

$$w_j, c \text{ unrestricted, } z_j > 0 \quad j = 1, \cdots, k \tag{2.15}$$

The MIP version of nonlinear formulation takes the form as below.

$$\underset{w_j, c}{Minimize} \sum_{i \in G_1} Y(d_{i1}^{+}) + \sum_{i \in G_2} Y(d_{i2}^{-}) \tag{2.16}$$

subject to $\sum_j w_j \cdot sign(a_{ij}) \cdot |a_{ij}|^{z_j} - d_{i1}^{+} + d_{i1}^{-} \le c$, $i = 1,..., n_1$ (Group1) (2.17)

$$\sum_j w_j \cdot sign(a_{ij}) \cdot |a_{ij}|^{z_j} - d_{i2}^{+} + d_{i2}^{-} > c, \; i = 1,..., n_2 \text{ (Group2)} \tag{2.18}$$

$$d_{ir}^{+}, d_{ir}^{-} \ge 0, \; i = 1,..., n_r, \; r = 1,2, \tag{2.19}$$

$$w_j, c \text{ unrestricted}, \; z_j > 0 \quad j = 1, \cdots, k \tag{2.20}$$

where all the setup is the same as those in section 2, except that z_j is the newly introduced parameter to capture classification function nonlinearity.

Compared to existing linear and second order models, the main advantage of this formulation is its greater adaptability to given data situations and consequently the higher classification performance. Either linear classification functions ($z_j = 1$) or highly nonlinear classification functions ($z_j > 2$) can be captured by this concise functional form. At the same time, the adaptability of this functional form eliminates the requirement of preliminary data analysis.

While attractive conceptually, the implementation of this nonlinear formulation is a challenging issue by itself. Conventional calculus based algorithms widely used in solving linear and nonlinear programming generally require convexity of the optimization problem to locate global optimality. When it comes to the proposed nonlinear MSD and MIP formulation, the convexity condition cannot be guaranteed when the z_j parameters in the constraint functions take any possible positive value. This non-convexity causes further complication in the mixed integer programming formulation. Some MP program solvers, like GAMS, have the ability to solve nonlinear programming problems, however, only to a limited degree. Nonlinear constraints are more difficult to deal with than linear ones and some literature suggests modelers should avoid nonlinear terms in equations to the extent possible (McCarl and Spreen, 2003). For a satisfactory solution of the proposed nonlinear formulations, we seek to use a robust optimization algorithm that can accommodate function irregularity and produce local or even global optimality as much as possible. Genetic algorithm is chosen for this purpose and some details of this algorithm are given below.

2.4 Genetic Algorithm for Global Optimization

First developed by John Holland (1962a, 1962b, 1962c, 1975, 1976, 1980, & 1992) and his colleagues, the genetic algorithm belongs to a family of so-called evolutionary algorithms based on the principles of natural selection. Since then, this approach has led to important discoveries in both natural and artificial systems in science, and its application spread across various fields, especially after the 1980s.

The fundamental ideas of the genetic algorithm come from the evolution process prevalent in nature—the survival of the fittest. Several unique concepts form the foundation of GA and distinguish it from conventional calculus based optimization algorithms.

Multiple Point Search and Parameter Coding

Conventional algorithms process no more than one point at a time. The optimal solution proceeds from one point to the next and a sequence of single points lead to the final local/global optima. Mimicking the evolution of species in nature, GA maintains a steady population of multiple individuals and operates on these individuals simultaneously at each step. This multiple point mechanism makes GA a parallel search algorithm and forms the foundation for GA's particular set of operations.

The individuals in the population are represented by strings. Unlike conventional optimization algorithms, GA does not deal with the optimization variables directly. Instead, the set of variables are coded into one finite-length string and the algorithm operates on such kind of strings. More than one possible way to code parameters exists, but binary strings are most commonly used in the genetic algorithm. For instance, a variable with a value of 25 will be represented by a binary string of 101001($1 \cdot 2^5 + 0 \cdot 2^4 + 1 \cdot 2^3 + 0 \cdot 2^2 + 0 \cdot 2^1 + 1 \cdot 2^0 = 25$). Multiple strings make up a generation.

After the first generation is initialized, the fitness[5] of each individual is evaluated as defined by the objective function. Once this value is obtained, the operators of the genetic algorithm take over and carry out such operations as reproduction, crossover, and mutation. This process continues until certain convergence criterion is met.

Operations: Reproduction, Crossover, and Mutation

Genetic algorithms function on strings through their operators. Reproduction, crossover, and mutation are three operators used by almost all genetic algorithms. For a current

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[5] In the genetic algorithm, the particular meaning of "fitness" is application specific. For instance, in a profit maximizing problem, the fitness is measured by profit. For a maximization problem, the greater the objective function, the greater the fitness value for a solution. The opposite is true of a minimization problem.

generation, after each individual (string) of the whole population is evaluated and assigned a fitness value, reproduction is applied. Reproduction creates new strings by making copies of strings from the current population according to the strings' fitness value. This in general means strings with higher fitness will have a higher probability of being passed on to the next generation. Once a string from the current generation is selected, the reproduction operator makes an exact replica of this string and enters this replica into a mating pool, constituting a base for production of the next generation. In nature, this corresponds to a creature's ability to survive predators, diseases, natural disasters or any other obstacles to reaching adulthood; this ability determines whether it will have the chance to reproduce and leave offspring.

After reproduction, crossover takes over. Crossover proceeds in two steps. First, "members of the newly reproduced strings in the mating pool" are paired at random; second, each pair of strings undergoes exchange as follows. An integer position k along the string is selected at random. Two new strings are then created by swapping all bits after position k. As an example, consider strings A1 and A2 in the mating pool: A1 = 001101 and A2 = 011000. Suppose $k = 4$ is obtained. All bits on both strings after the fourth one will then be exchanged. The crossover yields two new strings: A1' = 0011:00, A2' = 0110:01 (Goldberg, 1989).

The third operator introduced into GA is mutation. In a simple genetic algorithm, "mutation is the occasional (with small probability) random alteration of the value" (Goldberg, 1989) on bits of a string. In the case of binary coding, this means changing a 1 to 0 or vice versa. Mutation is needed, because, although reproduction and crossover are supposed to search and effectively recombine existing designs (strings), occasionally these designs may become dominant such that the 1s and 0s at particular string positions do not change, thus losing the potential of producing more valuable designs. The mutation operator is a scheme to protect against such an irrecoverable loss.

Besides parameter coding and multiple point searches, Goldberg (1989) pointed out GA's two more distinguishing features. First, GAs use only payoff (value of objective function) information, "not derivatives or other auxiliary knowledge". Second, "GAs use probabilistic transition rules to guide their search", not deterministic ones. To a certain degree these features slow down the GA in search, but on the other hand they contribute to GA's ability to realize global optimization and not be trapped by local minimums.

GA as a Global Optimizer

GA's capability as a robust global optimizer is documented in both applied and theoretical studies across fields. To name just a few, Dorsey and Mayer (1995) examined GA when applied to econometric estimation. GA was tested with multiple optima, nondifferentiability, and irregular problems and compared with four other methods: Nelder-Mead simplex, simulated annealing (SA), adaptive random search, and MSCORE. The overall results indicate GA's success in finding global or near global solutions and its advantage over the other methods. Ostermark (1999), through a hybrid version intended to reduce computation cost, examined GA on a set of highly irregular optimization problems. GA's ability to achieve global optimality is demonstrated on a set of six extremely complicated functions. Theoretical proof of GA's convergence to the global solution with any choice of initial population is provided by Bhandari et al. (1996). In this study, we adopt Genesis (Grefenstette, 1990) as the GA solver to solve the proposed nonlinear model and a typical flowchart of GA is presented in figure 2.1.

2.5 Data and Model Evaluation

Two data sets are used to evaluate the proposed model. The first data set is the set of data used by Ziari, Leatham, and Turvey (1995) that was collected by Canada's Farm Credit Corporation. This data set is from actual 1981, 1982, and 1983 loan applications for which loans were made in the Saskatchewan Province. All loan applications fall into two groups: group 1 of noncurrent loans, by individuals with recent histories of delinquent credit payments, and group 2 of current loans, by applicants without recent delinquent credit payments, based on the status of the loan as of March, 1990. The total sample of 1999 observations consisted of 754 current loan applications and 1,245 non-current loan applications.

The second data set is on the banking industry in Japan. This data was first published in "Financial Business (in Japanese)" (September, 1997, pp.44-47). A recent application of this data set was by Sueyoshi (2001) in a test of the DEA-Discriminant Analysis model. This data set contains the ranking of 100 Japanese banks based on a questionnaire survey at the beginning of 1997. For purpose of discriminant analysis, the 100 banks are divided into two groups, with the top 50 banks into group 1 (top) and the bottom 50 into group 2 (bottom).

In both data sets, each observation is described by seven attributes. Since we are more interested in the relative performances across the linear, quadratic, and nonlinear models, only four out of seven attributes are selected in our model. For the Canadian data, the four variables are liquidity ratio, rate of return on assets, debt-to-asset ratio, and repayment ratio; for the Japanese bank data, they are return on total assets, equity to total assets, cost-profit rate, and loss ratio of bad loan. The smaller attribute set is done to alleviate the degree of freedom problem associated with the second data set; also, the use of fewer variables reduces the search space and consequently the time needed for convergence in genetic algorithm.

Each data set is divided into two samples, one for model training and one for model validation, respectively. Following Ziari, Leatham, and Turvey’s paper, the first data set is divided in such a way that 60% (1,199 loans) of the total sample is selected by random sampling for model development and the remaining 40% (800 loans) for model validation. For the second data set of ranked observations, banks with odd number ranking are used for model training and the other 50 with even numbered ranking are reserved for model validation. Given our division of banks into two groups as above, training and validation sample have 25 top banks and 25 bottom banks respectively.

Model Evaluation Results

Based on the above two data sets, linear, quadratic, and the proposed nonlinear models are evaluated under MSD and MIP formulations. We report the results by two measures: the percentage of correct classifications and the value of the objective function. While the percentage of correct classification is the measure generally applied in DA literature, we believe that the objective value for a DA model is also important. The objective value directly measures how well an optimization model does the job it is designed to perform. This is particularly meaningful when a DA model goes beyond the number of correct classifications to seek minimizing the cost of misclassifying.

The results based on the Canadian credit scoring data are presented in table 2.1. The upper portion of this table reports the objective function value and classification results based on the training sample. For MSD formulation shown in row 1 to 3, quadratic model performs best in terms of total classification (57.8%), matched very closely by nonlinear model (57.7%), and the performance of linear model is lowest (52.3%). As the objective function (the sum of the deviations) is defined differently across the three models, it is not compared here for MSD formulation.

The results for MIP formulations are presented right below those for MSD formulations, shown for case 1, 2, and 3 respectively. In case 1, the objective function is defined as the number of total misclassifications (another way of saying correct classification). The linear model performs best, followed by quadratic model, and then nonlinear model. In case 2, the objective function is different from the measure of classification as unequal misclassification costs are introduced for current and noncurrent loans, with the misclassification cost of noncurrent loans two times that of current loans. Yet, both criteria give identical ordering on the performance of the three models: nonlinear model is the best, followed by quadratic model, and then linear model.

If we look further at the classification results of case 1 and 2, it is clear that three models classify much better on noncurrent loans than on current loans. This phenomenon is not so obvious for linear model in case 1, but as we put greater weight on misclassification of noncurrent loans in case 2, the same thing happens. Two observations are offered for this loss of discriminant power. First, this phenomenon seems to depend on the composition of sample. About 64 percent of this training sample is made up of noncurrent loans, which drives the model towards classifying all observations as noncurrent. For the Japanese bank data, the sample is equally divided between two groups and the loss of discrimination power never appeared. Second, this problem, if it is one, can be fixed by adjusting weight on the misclassification cost. In case 3, we do so by multiplying the misclassification of current loans by 2, then the classification of all observations into noncurrent loan group disappears. For case 3, in terms of model comparison, linear and quadratic models perform better than nonlinear model and this is so by either objective function or the percentage of correct classification.

The classification results based on validation sample are reported in the lower portion of table 2.1. Except a few cases, the three models tend to achieve lower classification rates compared to the training sample case, especially for MIP formulation. The relative orderings among three models also change from the training sample case.

We now move on to the results based on the Japanese banking data shown in table 2.2. The upper and lower portions of this table show the results based on the training sample and validation sample respectively. Briefly, like in Canadian data, each of the three models performs best in certain cases, but none of them dominates. For the proposed nonlinear model, except in case 3 for MIP formulation, it shows the best performance among the three models, by either objective function or total correct classification criterion. This seems better than it does in Canadian data.

To get a clearer picture of their relative performance, we further summarize the results below. In each group of the table wherein a comparison can be made among three models, by each measure, the best model will receive a point of 3, the second best model 2, and the worst model 1. For example, based on the Canadian credit scoring data (table 2.1) and MSD formulation, the quadratic model gives the highest classification performance of 693 in the training sample, and is assigned a point of 3, followed by 2 and 1 for the nonlinear and linear models, respectively. Such points are given in each group and summed up across MSD formulation and the three cases of MIP formulation for the linear, quadratic, and nonlinear models, respectively.

Results of this more inclusive measure are reported in table 2.3. By this measure, based on the Canadian credit scoring data, the nonlinear model is the winner in objective function value for the training sample, but it is beaten by the linear model in the validation sample; in terms of classification, the nonlinear model is the clear winner among the three in both the training and validation samples. The relative ranking between the linear and quadratic models is mixed. However, a sum of points across columns puts the linear model ahead of quadratic model (30 over 22). The lower section of table 2.3 gives the measure based on the Japanese bank data. The nonlinear model is the winner by either objective function value or classification performance in both the training and validation sample. Again, the ranking between the linear and quadratic models is mixed, while a sum of the points indicates the quadratic model as the better one (26 over 24).

Discussion

The mixed ranking between the linear and quadratic models across the two data sets is consistent with the study by Silva and Stam (1994). They suggested that the quadratic model may not be suited for particular data conditions and in that case linear model will perform better than the quadratic one. The performance of the two models demonstrated here provides more evidence of this result.

The relative performance of the nonlinear model is more puzzling. If the nonlinear problem can be solved completely, i.e. global optima found, we would expect the nonlinear model to beat—or at least be as good as—the other two in all cases, especially in terms of objective value. This is so because conceptually, if there exists a better solution realized by either the linear or the quadratic model, the nonlinear model should be able to reach that solution by adjusting their power parameters to 1 or 2, driven by the optimization algorithm. However, this is not the case we observed. For example, in table 2.1, linear MIP reaches a misclassification cost as low as 387, but the nonlinear MP gets just 435. This is a fall below our expectation and it leads us to suspect the solver's effectiveness in reaching global optimality, at least in our particular situation[6].

[6] The solver's effectiveness puts qualification on the results reported here. Specifically, the solver's problem may happen for three reasons, including human errors in the use of Genesis (the software), limitations with Genesis, or the limitations with genetic algorithm in this particular situation. Given the widely reported robustness of genetic algorithm, further research may first begin with using another genetic algorithm software more recent than Genesis, to verify or exclude the first two possibilities.

2.6 Concluding Remarks

Since MP was introduced into DA in the early 1980s, MP based DA models have generally adopted the linear form of classification function, the exception being the Silva and Stam (1994) quadratic model that surpasses the linear model in certain cases. We have shown in this study the research potential of a new type of classification function for MP based DA models. Particularly, we propose a more generalized nonlinear model that allows for flexible degrees of nonlinearity and attempts to solve the resultant nonlinear problem using robust global optimization genetic algorithm. Based on two sets of real financial data, the proposed model is evaluated against the linear and quadratic model under MSD and MIP formulations. The results show that across both data sets, each of the three models takes lead in certain cases, but overall, the proposed nonlinear model appears to be the most effective of the three.

Continued study of this nonlinear model is warranted. First, a robust optimization algorithm is critical to the nonlinear approach. The proposed model performs relatively well based on the genetic algorithm, yet it falls below our original expectation. It appears that the genetic algorithm we applied has not fully solved the nonlinear problem proposed. Robust global optimization algorithms other than the genetic algorithm are worth trying to find out if any of them can perform better in this situation and consequently achieve the full potential this nonlinear formulation can offer. Second, when global optimization is established, further tests of this model based on real data from other fields or simulation data would be desirable for a more comprehensive evaluation of its performance.

CHAPTER III

THE RELATIONSHIP BETWEEN AGGREGATE BUSINESS FAILURES AND MACROECONOMIC CONDITIONS

3.1 Introduction

An understanding of what causes business failure (or bankruptcy, interchangeably henceforward) has received considerable attention in the past few decades. At the micro level, understanding why and whether particular firms fail is useful for the prediction and prevention of financial distress for other firms. The micro line of research is extensive and usually involves the use of firm-specific information to predict firm failure. A partial list of papers include those by Beaver (1966); Altman (1968); Ohlson (1980); Altman and Izan (1984); Zmijewski (1984); Lennox (1999); Shumway (2001); Chava and Jarrow (2004). At the macro level, knowing what variables cause aggregate business bankruptcies is useful to authorities of state and federal agencies making macro policies.

Relatively less attention has been paid to the macro line of research. Due to lack of well-developed economic theory, previous empirical studies in this regard have relied on economic intuition, microeconomic theory, or statistical analysis for a conceptual framework. Based on analysis of vulnerable firms, Altman (1971, 1983) studied business failure rate as determined by four conditions, including real economic growth, credit or money market condition, stock market activity, and business population characteristics. Rose et al. (1982) started with a wide spectrum of macroeconomic indicators and reduced them into a compact set of six variables via statistical analysis: the SP500 index, the prime rate, the 90-day treasury bill rate, and three non-monetary supply and demand factors. Deviating from the approach using multiple intuitively chosen variables, Melicher and Hearth (1988) proposed aggregate business failures as only a function of financial markets, especially credit market conditions. Three variables, interest rate levels and volatility, credit availability, and stock market index are studied in their work. Drawing on the shutting-down condition in neoclassic microeconomic theory, Platt and Platt (1994) studied aggregate corporate failure as a function of general cost and economic conditions (revenue benchmark). Most recently, Liu (2004) studied the British experience, considering interest rate, lending to the corporate sector, corporate profit, retail price index, and corporate birth rate as the determinants of corporate failures. Her study extended the literature with a description of the long-run relationship by using the error correction model.

Among all the studies, the empirical literature seems to have reached nearer consensus on certain variables, including corporate profits, and interest rates. There is little consensus and much conflicting opinion regarding the other variables, particularly inflation and stock market performance.

Two considerations motivate this study. First, as mentioned above, while existing studies have provided much insight, the impacts of certain important macro variables on aggregate business failures, especially inflation and the stock market index, are not clear or inconsistent among existing studies. Second, causation and correlation are two different concepts and the distinction should be important to the discussion of any relationship. However, such a distinction has not been drawn clearly in literature. Most studies usually seek to find the determinants of business failures and identify a set of macro economic variables based on analysis of firm failures at a micro level. While there is a good reason to believe these variables are related to aggregate business failures, it is questionable that the same causal relationship that holds at the micro level necessarily holds at the macro level. For example, aggregate business failures may not be such a passive dependent variable as usually assumed; it may also play a proactive role in the overall economy (Bernanke, 1981). In fact, earlier literature suggests that the liability measure of business failures leads general business cycle (Moore, 1950; Simpson and Anderson, 1957). Given the different findings and the lack of a widely accepted theory to provide a structural foundation, empirical studies should be careful in the establishment of causality in this context.

This study evaluates the relationship between business failures and macroeconomic conditions with special attention paid to causality. A set of relevant macroeconomic variables are first identified and then the relationship analyzed in a structural Vector Autoregression (VAR) using techniques of innovation accounting. Originated in artificial intelligence and computer science, Directed Acyclic Graphs (DAG) and algorithms of inductive causality are recent innovations that help researchers solve the problems in economics and finance, particularly where causality is not established by theory. Assuming no a priori causal structure, we rely on DAG and the inductive causality algorithms to provide a “data-driven” causal structure that is incorporated into the analysis of structural VAR. As shown by Swanson and Granger

(1997) and more recent literature (Awokuse and Bessler, 2003; Bessler and Yang, 2003), this “data-driven” approach may produce more objective analysis than those based on Choleski decomposition of observed innovations or a structural model of innovations based on subjective grounds.

This study is presented as follows: Section 3.2 introduces the conceptual structure and the data used. A description of the DAG and time series methods follows in section 3.3. Section 3.4 presents implementation, empirical findings, and discussion. Section 3.5 concludes the chapter.

3.2 Conceptual Framework and Data

There is more than one variable to represent the business failure activity at the macro scale, including the business failure rate in percentage (Altman, 1983), the business failure in numbers (Melicher and Hearth, 1988), and the liabilities measure (Moore, 1950). We choose the business failure in numbers (or aggregate business failures, interchangeably) in our study for two considerations. First, business failures and births account for a very small portion of total business numbers and business failure in numbers mimics the time series behavior of business failures in percentage (Chava and Jarrow, 2004). Meanwhile, business failure numbers as an absolute measure is closer to the business failure liabilities (via the average liability of business failures), which enables a closer comparison of our finding to previous studies using business failure liabilities.

We then identify relevant macroeconomic variables based on analysis of individual business failures. An analysis of the failure of individual firms would suggest that particular macroeconomic variables potentially influence business failures, including economic growth, monetary condition, inflation, and stock market performance. This approach to identify related macro variables is essentially the same as that followed in Altman (1983), Liu (2004), and Platt and Platt (1994), among others[7]. However, we deviate from previous studies by not imposing any a priori causal structure in our following analysis. Before we allow data to reveal themselves in the following analysis, we present the rationale for including the selected macroeconomic variables in our study.

First, economic growth is considered important as it may have direct influence on a firm's sales and earnings. The latter are a direct measure of a firm's current performance and provide the cash flow critical to the firm's continued survival. An overall economic index like GNP and aggregate corporate profits may both be used for this condition (Altman, 1983). We chose aggregate corporate profits in this study. Instead of GNP, aggregate corporate profits are chosen because they directly measure the business health of firms. Also, it is used extensively in the literature and usually has been found significant and negatively associated with business failures.

[7] While these studies all identify macro variables by starting with an examination of individual firm failure, the macroeconomic variables selected in each study vary. The variables chosen in our study are closer to those in Altman (1983) and Liu (2004). Compared to these two studies, we place less emphasis on the composition of business failures and have not included new firm formation variables; also, we have included inflation (versus Altman (1983)) and stock market performance (versus Liu (2004)).

Money, or credit availability and its cost, is another factor that is thought to have a direct impact to a marginal firm's survival. "Regardless of how poorly a firm is performing, it seldom is motivated to declare bankruptcy as long as liquidity is sufficient or credit is available" (Altman, 1983). It is then reasonable to expect that the propensity to fail will be increased during periods of relatively tight credit conditions. Following other studies, interest rates are used in this study to capture monetary conditions.

The role that inflation plays in aggregate business failures is less clear than the above two conditions. Generally, inflation is an important indicator of overall economy. Without giving empirical evidence, Altman (1983) postulated that inflation, especially unanticipated price increases, "tend to be inversely correlated with failure rates," as leveraged firms can repay their debts with "cheaper" money, and also because of the reduced competitiveness caused by inflation. On the other hand, Wadhwani (1986) and Liu (2004) found empirical evidence that inflation leads to more business bankruptcies. Thus, inflation is included as a third variable that may affect aggregate business failures.

Stock market performance is the forth factor to consider. Altman (1983) argued that stock market performance affects firm failures for two reasons. First, a potential failing firm will not go bankrupt "if the future appears hopeful" and the future may be indicated by investor expectations, or stock market performance. Second, by definition, bankruptcy occurs where "the firm's liabilities exceed the economic value of its assets." The market value reflects economic value, thus, a drop in stock price can be an immediate cause of failure, and this is just more likely to happen in bearish market conditions. In existing studies, stock market performance, represented by S&P 500 index, has been found to lead business failures; however, conflicting findings remain regarding its sign (Rose et al, 1982; Altman, 1983; Melicher and Hearth, 1988).

Five U.S. quarterly data series, measured over 1980 to 2004 in U.S. with a total of 100 observations, are used to represent the five variables discussed above. Total business bankruptcies number (BANKB) is used to measure the aggregate business failures in the U.S. The other four variables, corporate profits (CORPP), 3-month T-Bill yield (INT), producer price index of all commodities (PPIACO), and S&P500 stock index (SP500), are used to reflex economic growth, money supply and credit condition, price level, and investor expectation respectively.

The five data series come from the following sources: total business bankruptcies from Office of U.S. District Courts, corporate profits from Bureau of Economic Analysis, interest rate from Federal Reserve Bank, producer price index of all commodities from Bureau of Labor Statistics, and S&P500 index from Standard & Poors. All these data were accessed from www.economy.com in December 2005. Analysis of these data follows the presentation of empirical methodology in the next section.

3.3 Empirical Methodology

The multivariate time-series analysis method of vector autoregression (VAR) is the basic framework we use. Also, directed acyclic graph is used to provide a contemporaneous causal structure for VAR. A description of this combined approach is given below.

Vector Autoregression

The five data series are modeled as Vector Autoregression. Since Sims (1980), VARs have been studied widely to investigate the relationship between macroeconomic variables. Compared with earlier approaches in the construction of large-scale structural models, VARs provide a way to "estimate large-scale macromodels as unrestricted reduced forms, treating all variables as endogenous." (Sims, 1980)

For a system of N (N = 5 in this study) variables with p lags, the VAR model *in a standard or reduced form* is represented as

$$Y_t = A_0 + \sum_{i=1}^{p} A_i Y_{t-i} + e_t \, (t = 1, ..., T)$$

where Y_t is a vector of N variables at time t, A_0 is a vector of N constants, A_i is a $N \times N$ matrix of coefficients for the i_{th} lagged period, and e_t is a vector of residuals. Ordinary least squares, applied separately to each question, provide efficient and consistent estimates of the unknown parameters, A_0 and the A_i s.

The coefficients in VARs are difficult to interpret. We summarize the relationship among the studied variables using innovation accounting techniques, i.e., impulse response function (IRF) and forecast error variance decomposition (FEVD). The IRF, VAR in a Vector Moving Average (VMA) representation, allows us to trace the impacts of structural shocks on the variables in the system; the FEVD, on the other hand, reveals the proportion of the movement in a variable due to its own shocks versus shocks of the other variables in the system. To use either of these two, however, we need to recover the structural shocks, not the residuals from reduced form VAR (Enders, 2004).

One solution to this problem is through decomposition of the covariance matrix (contemporaneous correlations) of the residuals (Swanson and Granger, 1997). Following Sims (1986), the relationship between structural shocks and the estimated VAR residuals can be modeled as $Be_t = u_t$ where B is a N×N matrix. In this case of N = 5, this relationship can be shown as

$$\begin{bmatrix} 1 & b_{12} & b_{13} & b_{14} & b_{15} \\ b_{21} & 1 & b_{23} & b_{24} & b_{25} \\ b_{31} & b_{32} & 1 & b_{34} & b_{35} \\ b_{41} & b_{42} & b_{43} & 1 & b_{45} \\ b_{51} & b_{52} & b_{53} & b_{54} & 1 \end{bmatrix} \cdot \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \\ e_{5t} \end{bmatrix} = \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \\ u_{5t} \end{bmatrix}$$

where b_{ij} are the contemporaneous correlation parameters to be estimated or restricted to be zero, as discussed below; e_{it} represent the observed residuals in the above standard form VAR model; and u_{it} represent the underlying shocks in the structural model.

It has been common in VAR analyses to use Choleski decomposition. By the use of Choleski decomposition, matrix B is assumed a lower triangular form. In our case, such a lower triangular B matrix will take the form below

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ b_{21} & 1 & 0 & 0 & 0 \\ b_{31} & b_{32} & 1 & 0 & 0 \\ b_{41} & b_{42} & b_{43} & 1 & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & 1 \end{bmatrix} \cdot \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \\ e_{5t} \end{bmatrix} = \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \\ u_{5t} \end{bmatrix}$$

By forcing $(n^2 - n)/2$ values of B matrix to equal zero, Choleski decomposition achieves a just-identified system in contemporaneous time. However, such a decomposition forces a unidirectional causal ordering such as

$y_1 \rightarrow y_2 \rightarrow y_3 \rightarrow y_4 \rightarrow y_5 \cdots$, which oftentimes is not the true, and therefore leads to misleading results.

Alternatively, structural VAR can be used for decomposition (Bernanke, 1986). "The aim of a structural VAR is to use economic theory (rather than the Choleski decomposition) to recover the structural innovations from the residuals" (Enders, 2004, p.292). Structural VAR does not require a recursive structure and presents a general framework of modeling the contemporaneous causal flows, however, a predetermined structural theory is still indispensable (Swanson and Granger, 1997).

The aggregate business failures causality issue examined here is just such a situation wherein no predetermined contemporaneous causal structure can be used. We rely on data-driven approach based on DAG for identification and incorporate this information into a frame of structural VAR. Some details of DAG are given below.

Directed Acyclic Graphs

Experimental data is rare in economics and causation, versus correlation, is in general difficult to assign. Arising from the field of artificial intelligence, DAG is one tool developed to learn about causation from observational (non-experimental) data.

Put simply, directed graphs are pictures representing the causal flows among a set of variables. Formally, a directed graph can described by an ordered triple (V, M, E), where V is a nonempty set of vertices standing for variables studied, M is a nonempty set of symbols attached to the end of undirected edges, and E is a set of ordered pairs. Variables connected by an edge are said to be adjacent. Consider two variables A and B among a set of variables V, they may be associated by different types of graphs: (i) a undirected graph contains only undirected edges (e.g. A-B); (ii) a directed graph contains only directed edges (e.g. A->B); (iii) an inducing path graph contains both directed and bidirected edges (A<->B); (iv) a partially oriented inducing path graph contains directed edges (->), bidirected edges (<->), non-directed edges (o-o) and partially directed edges (o->). A directed acyclic graph is a graph that contains no directed cyclic paths (an acyclic graph contains no variable more than once) (Spirtes, et al., 2000). Only directed acyclic graphs are considered in this study.

Directed acyclic graphs are designs for representing conditional independence as implied by the recursive product decomposition:

$$\Pr(v_1, v_2, v_3, ..., v_n) = \prod_{i=1}^{n} \Pr(v_i \mid pa_i)$$

where $\Pr$ is the probability of variables $v_1, v_2, v_3, \ldots, v_n$, and pa_i is the realization of some subset of the variables that precede (cause) v_i in order ($v_1, v_2, v_3, \ldots, v_n$). Pearl (1986) proposed d-separation as a graphical characterization of conditional independence. A proof of this proposition was given by Verma and Pearl (1988). Spirtes, Glymour, and Scheines (2000) incorporated the notion of d-separation to develop the algorithms for building directed graphs.

Details about the basic algorithm (PC algorithm) and its more advanced versions can be found in Spirtes, et al. (2000) and are not explored here. Put very simply, the algorithm begins with a complete undirected graph G, where an undirected edge exists between every variable in the variable set V. Edges between variables are removed sequentially based on zero correlation or partial correlation (conditional correlation) and the remaining edges are 'directed' using the concept of sepset, to be explained below.

To test whether partial correlations are significantly different from zero, Fisher's z is used, $z(\rho(i,j|k)n) = 1/2(n-|k|-3)^{1/2} \cdot \ln\{(|1+\rho(i,j|k)|)\cdot(|1-\rho(i,j|k)|)^{-1}\}$, where n is the number of observations used to estimate the correlations, $\rho(i,j|k)$ is the population correlation between series i and j conditional on series k (removing the series k's influence on series i and j), $|k|$ is the number of variables in the series. If series i, j, and k are normally distributed and $r(i,j|k)$ is the sample conditional correlation of i and j given k, then the distribution of $z(\rho(i,j|k)n)$ - $z(r(i,j|k)n)$ is also standard normal.

For two variables whose edge has been removed, the sepset refers to the conditioning variable(s) on the removed edge between two variables. So if the edge between variables A and B is removed by conditioning on variable E, then E is the sepset of A and B. To illustrate how to direct edges, consider a triple X-Y-Z wherein X and Y, Y and Z are both adjacent, but X and Z are not. The edges are directed as X->Y<-Z if Y is not the sepset of X and Z. If the edge between X and Y has been directed as X->Y, Y and Z are adjacent, X and Z are not adjacent, and there is no arrowhead at Y, then Y-Z edge is directed as Y-> Z. If there is a directed path from X to Y and an edge between X and Y, then direct X-Y as X->Y. The above sequential procedures are programmed and available in TETRAD II (Scheines, et al., 1994). TETRAD IV, a more advanced version of TETRAD II, is used in our study.

Based on the Monte Carlo simulations of PC algorithm (Spirtes, Glymour, and Scheines, 2000; Demiralp and Hoover, 2003), for sample sizes of 100, PC algorithm may make two types of mistakes: edge exclusion or inclusion and edge direction (direction of edges); the latter appears to be more likely than the former. Spirtes, Glymour, and Scheines suggested that "In order for the methods to converge to correct decisions with probability 1, the significance level used in making decisions should decrease as the sample size increases and the use of higher significance levels (e.g., 0.2 at sample size less than 100, and 0.1 at sample size between 100 and 300) may improve performance at small sample sizes." (Spirtes, Glymour, and Scheines, p.116). Following their suggestions, the DAG results at 0.2 significance levels are mainly used in this study.

3.4 Empirical Results

The five data series were first tested with augmented Dickey-Fuller test and were all found to be nonstationary (see table 3.1). We then search for the existence of cointegration in the variables. Before the use of trace test, an optimal lag for the five variables is selected by minimizing Schwarz loss and Akaike loss criteria. For the first difference VAR, as shown in table 3.2, Schwarz and Akaike loss criteria give the optimal lag of 1 and 3 respectively. A lag of 1 is chosen for our analysis based on parsimony principle. Further, we follow the trace test of Johansen to determine the rank of cointegration. Based on the test results reported in table 3.3, there are three cointegration vectors with a linear trend among the five variables.

The five series are then estimated using Error Correction Model. The innovation correlation matrix obtained from this model is as below (correlation elements are presented in the order listed across the top of the *Corr* matrix):

$$
\begin{array}{cccccc}
 & \text{BANKB} & \text{CORPP} & \text{INT} & \text{PPIACO} & \text{SP500} \\
Corr = & \left[\begin{array}{ccccc}
1.0000 & & & & \\
-0.0370 & 1.0000 & & & \\
-0.2385 & 0.0981 & 1.0000 & & \\
-0.0426 & 0.0158 & 0.3290 & 1.0000 & \\
-0.0761 & 0.1883 & 0.0798 & -0.0957 & 1.0000
\end{array}\right] & & & &
\end{array}
$$

In this matrix, the correlations between BANKB and INT, CORPP and SP500, INT and PPIACO are among the strongest. The remaining correlations are much weaker. This correlation matrix was used as a starting point for obtaining the contemporaneous causation based on DAG. The matrix is processed by TETRAD (Scheines *et al*., 1994) without a priori knowledge of causal relationship among the five variables. Using PC algorithm, TETRAD proceeds with a complete set of undirected edges connecting each of the 5 vertices, edges are removed if a correlation or conditional correlation is not significantly different from zero for given significance level. The remaining edges are directed by sepset conditions. The resulting directed graphs, at two levels of significance for removal of edges, are given in Figure 3.1.

Given the number of observations in this case, a significance level of 20% is appropriate (see the Monte Carlo results described in Spirtes, Glymour and Scheines, 2000). At this level, shown in panel A, there are two directed edges. One directed edge shows a causal flow from BANKB to INT and the other is from PPIACO to INT. In addition, there is the edge between CORPP and SP500, but it is not directed. For a check of robustness, we go further to a higher significance level of 30 percent. At this level, the DAG pattern is identical to that at 20 percent. The causal flow from PPIACO to INT suggests that inflation contemporaneously causes interest rate, something we expect of interest rate as a policy tool in responding to inflation. Given the literature seeking the determinants of business failures, a contemporaneous causal effect of business failures on interest rate would not be well expected. However, if aggregate business failures represent risk, it then follows naturally from finance theory that interest rate will factor this in as a risk premium, making this causal flow reasonable. Based on Bernanke (1981), bankruptcy represents a cost that lenders avoid by being more selective or cautious in giving out loans. This explanation appears to offer a specific mechanism for aggregate business failures to impact on interest rate. The above said, these causal relationships are only contemporaneous and do not necessarily hold over longer horizons, and we depend on innovation accounting for further insight.

As for the undirected edge between CORPP and SP500, insufficient information or a lack of true contemporaneous causality may be the reason (this also explains the lack of edge between two variables). As we expect that the stock market would be a reflection of economic activity (represented by CORPP), we tend to accept a causal flow from CORPP to SP500 based on finance theory. Meanwhile, we do conduct the DAG analysis at a higher significance level of 40% and this edge then becomes directed from

CORPP to SP500[8]. Based on the above considerations, we use the edge as directed from CORPP to SP500. This edge, along with the directed edge from BANKB to INT, and PPIACO to INT, constitute the contemporaneous causal structure to be used in the following innovation accounting analysis.

Impulse Response Functions

Impulse response functions are first presented in figure 3.2 as part of the innovation accounting analysis. The responses of all the 5 variables (standardized to be on the same scale) to a one time unit shock from itself or other variables are shown individually by one of the 25 small graphs. Unlike contemporaneous pattern revealed by DAG, the impulse response functions show the causal relationships over a longer horizon (up to 20 quarters in this case). The five variables giving out shocks are listed on top of the figure from column 1 to 5. The responses of all the 5 variables to each variable shock are shown in a column from row 1 to 5.

In column 1, to such a positive shock (or innovation, interchangeably) of BANKB, the response of CORPP is negative and lasts over long period. SP500 also responds negatively to this CORPP shock and the response becomes increasingly significant over time. However, the other two variables, INT and PPIACO, are not impacted. The effects of BANKB on CORPP and SP500 appear puzzling at first, because at the firm level, profitability usually determines the occurrence of bankruptcy. At the macro level, the picture may be different. As part of Bernanke (1981) story, in a

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[8] We also conducted impulse response function and forecast error variance decomposition based on the reverse direction (from SP500 to CORPP). The results are not significantly different.

process of recession propagation, economy wide bankruptcy risk generates a general attempt to ensure solvency, which leads to reduced demand from both consumers and producers and deepens recession. This story seems to help explain the observed responses by CORPP and SP500.

The responses to a CORPP shock are shown in column 2 (Figure 3.2). A positive CORPP shock has a negative impact on BANKB, but it is almost negligible. Also, INT does not respond visibly to such a shock. The response of PPIACO is positive over shorter horizon and then negative in longer term, but the response is limited. SP500 responds positively to this shock and the significant response lasts through the whole horizon. While the effects of CORPP on PPIACO and SP500 are expected, the lack of response from BANKB deviates from our expectation (more precisely, based on previous studies seeking the causes of business failures), but is more in line with the structural role postulated by Bernanke (1981), and the findings by Moore (1950).

Column 3 records the responses to a shock in INT (Figure 3.2). To varying degrees, INT shock affects all the other four variables. BANKB shows a modest positive response that lasts over long horizon. CORPP, on the other hand, responds negatively to an INT shock and the response is lasting. The response of PPIACO is also negative and lasts through the whole horizon. SP500 shows a minor positive increase in short run and then the response drops to be negative later. The responses of CORPP, PPIACO, and SP500 are not surprising given the role of interest rate in controlling inflation and stabilizing economy growth. Particularly, the positive response of BANKB seems to verify previous findings on the importance of monetary condition to business failures.

That is, higher interest rate means credit is less available or more costly, which increases the propensity of failure for vulnerable firms.

In the fourth column, in response to a PPIACO shock, BANKB shows only negligible fluctuations (Figure 3.2). The response of CORPP is overall negative, bouncing back to normal as time goes by. INT responds to PPIACO shock first positively for a period of 3 quarters and then negatively over longer horizon. SP500 shows a negative response and the significant response lasts over time. The negative responses of CORPP and SP500 may have been caused by PPIACO itself (representing high inflation), or indirectly, via the action of INT (interest rate) which responds first positively to PPIACO shock (recall the contemporaneous causal flow from PPIACO to INT) and then exerts its influences on CORPP and SP500.

Finally, the fifth column records the responses to a shock in S&P 500 index (Figure 3.2). BANKB does not appear to be affected much by a positive SP500 shock. The response of CORPP is obviously negative and through long horizon. The responses of INT and PPIACO are different in magnitude but similar in pattern: first positive and then dropping (to normal or negative level). A possible explanation may be, a booming economy, represented by booming stock market, triggers higher inflation and consequently higher interest rate (recall the contemporaneous causal flow in DAG), which in turn leads to a somewhat contained growth and more stable price level.

Forecast Error Variance Decomposition

Forecast error variance decomposition results are presented in table 3.4. Listed in the table for each variable (in a section) are 7 steps of 0 (contemporaneous time), 1, 2, 5, 10, 15, 20 quarters ahead. For each step, the entries show the percentage of variation of a variable that is due to innovations by itself and the other four variables. In addition to impulse response functions, forecast error variance decomposition offers an alternative way to look at the relative exogeneity (or endogeneity) of the variables.

Briefly, as can be observed in table 3.4, BANKB appears to be an exogenous variable among the five variables, but it is also explained by INT increasingly over longer horizon, up to a portion of 15 percent. INT and PPIACO are also relatively exogenous (versus CORPP and SP500), and they are intertwined with each other with each explaining significant portion of the other's variance (from 20 to 30 percent). It is worth noting that BANKB explains little of INT and PPIACO, but SP500, on the other hand, explain up to 10 percent of the variance of these two variables.

CORPP and SP500 appear to be the less exogenous variables of the five. Either of them is subject to significant influences from INT and PPIACO combined (over 40 percent). Between these two, CORPP appears to be the more exogenous. CORPP explains over 30 percent of SP500 variance while SP500 explains about only 10 percent of CORPP variance at longer horizon. Further, BANKB explains considerable portions of CORPP and SP500 variance (17 and 10 percent respectively). Overall, these patterns are consistent with the results shown by impulse response functions.

3.5 Concluding Remarks

This study investigates the causal relationship between aggregate business failures and macro economic variables. Based on quarterly US data from 1980 to 2004, aggregate business failures, aggregate corporate profits, interest rate, inflation, and S&P 500 are studied in an approach that combines structural VAR and directed acyclic graph. Specifically, DAG is used to provide for VAR a contemporaneous causal structure not available from theory. The VAR estimation results are then summarized using impulse response function and forecast error variance decomposition. Among others, the results suggest that aggregate business failures appear to be an exogenous variable among the five; meanwhile, it is subject to the influence of interest rate.

A central finding of this study is the exogeneity of aggregate business failures. This is surprising at first given its deviation from the applied line of studies that seek the determinants of business failures. We ascribe this deviation to the data-driven approach we have followed. If we begin with an intention of finding out what variables determine business failures and impose this intention as a causal structure, we would have precluded the possibility of business failures as a proactive factor. Moreover, the exogeneity of aggregate business failures is consistent with the postulation by Bernanke (1981). Also, this exogeneity is consistent with earlier findings on business failures liabilities as a leading indicator by National Bureau of Economic Research (Moore, 1950). Of course, this issue is subject to further test. As one possibility, further research may proceed by examining empirically the structural story laid out in Bernanke (1981).

Most of our findings are consistent with other studies. Our results find that interest rate influences aggregate business positively, lending support to previous studies in this regard (Melicher and Hearth, 1988; Liu, 2004). This information is important to policy makers because it shows that credit availability is critical to the survival of marginal firms and interest rate can be used as an instrument when the control of bankruptcy risk is a policy target. The importance of interest rate a policy tool is not limited to bankruptcy risk. By our findings, interest rate also plays an important role in its interactions with economic growth, inflation, and stock market.

CHAPTER IV

THE INCLUSION OF MACROECONOMIC VARIABLES IN BUSINESS FAILURE PREDICTION: THE CASE OF THE U.S. AIRLINE INDUSTRY

4.1 Introduction

This chapter studies macroeconomic variables in business failure prediction models. Since Beaver (1966) and Altman (1968), a constantly growing literature has been devoted to the prediction of business failures, including those reporting statistical procedures, and those searching for appropriate variables. While statistical procedures and choice of variables are both indispensable for a successful prediction, the choice of variables may be the more basic issue, and probably more important in the sense that the predictive powers of linearly transformed variables have been shown to be robust across different estimation procedures (Ohlson, 1980).

A wide array of variables has been presented in literature for business failure prediction. From the very beginning, firm specific variables provide the primary source of information for failure prediction. The particular variables used are seldom the same from study to study, but firm financial variables, or so-called accounting based financial ratios, are the most commonly used, reflecting a firm's profitability, leverage, and liquidity. In addition, firm specific information also comes from non-accounting sources, e.g., a firm's equity value from financial markets.

Since 1980s, industry specific information has been found to provide information not contained in firm specific variables. Industry specific information is useful for two reasons. First, the usual levels of financial ratios are different between industries because of the difference in industry structure and accounting rules. Second, different industries may not experience boom or recession at the same time. Problems thus arise when firms from different industries are pooled together, or models based on firms from one group of industries are used to predict firms in other industries. Industry relative ratios or dummies have been suggested to solve this problem (Platt and Platt, 1990, 1991; Lennox, 1999) and a more recent study on the incorporation of industry effect is provided by Chava and Jarrow (2004).

Besides industry specific information, existing literatures also began to introduce macroeconomic effect into business failure prediction since the 1990s. This extension appears reasonable. Economic intuition tends to suggest that a firm’s propensity to fail is influenced by economic cycles and this intuition is supported by empirical studies at the macro level (Altman, 1971; Liu, 2004). A partial list of studies incorporating macroeconomic effect includes those by Kane et al. (1996), Richardson et al. (1998), Lennox (1999), Tirapat and Nittayagasetwat (1999), Duffie and Wang (2004), and Hunter and Isachenkova (2006). Various indicators, including business confidence index, economic growth, inflation, interest rates, personal income growth, exchange rate, or their changes, are covered in the above failure prediction models.

Despite the current use of macro variables in failure prediction, few studies have evaluated the effect of macroeconomic variables on prediction accuracy. This leaves a question unanswered: whether, or how much, is the inclusion of macro variables actually useful to failure prediction? This question is justified because firm financial ratios are subject to the influence of macro economic conditions and they are already part of the prediction model. What the macro variables can add is another question and should be subject to empirical testing. An answer to this question matters generally and is more useful when it comes to the choice of particular macro variables. In this chapter, using the U.S. airline companies as a case study and logit as the statistical technique, we contrast a model augmented with macro variables to the model using only firm level information. The incremental information content of macro variables to failure prediction is the main hypothesis we test in this study.

We focus our attention on the effect of a few general macroeconomic indicators. Particularly, economic growth, interest rate, and inflation are considered as potential candidates in failure prediction modeling. The selection of this initial set of variables is inspired by the studies about the aggregate business failures and macro economy relationship (Altman, 1971; others). Kane et al. (1996) and Richardson et al. (1998) studied whether the inclusion of economic recession is incrementally informative to the prediction of corporate failures. This study differs from theirs in the use of more general macroeconomic conditions, and is closer to the work by Hunter and Isachenkova (2006).

As a second feature, this study evaluates the effect of macro variables on firm failure prediction using only the airline firm data. The selection of observations from single industry is meant to skip the possible industry effect and to focus on the macro effect. A simultaneous consideration is that by proceeding from one industry to another in future studies, we will be able to observe the different effects of macro economic conditions across industries. These firm data are obtained from Mergent Online. The airline industry sector in Mergent Online provides a total of 42 firms, covering a period from 1990 to 2005.

The rest of this chapter proceeds as follows. Section 4.2 develops briefly a rationale regarding the use of macroeconomic variables in failure prediction. Section 4.3 describes the data and methodologies applied, including data, sampling designs, and statistical model. Section 4.4 presents the estimated model and validation results; a summary and discussion of further research concludes the chapter in section 4.5.

4.2 Development of Hypothesis

Conceptually, the use of macroeconomic variables in failure prediction is not justified in all cases. Altman (1982, p. 98) suggested that failure prediction models cannot directly use macroeconomic variables as additional explanatory variables, if the traditional paired sample approach is followed. The reason is because when failed and nonfailed firms are matched one by one in terms of industry and year, macroeconomic conditions are identical for failed and nonfailed firms, offering no discriminatory power. Jones (1987) suggested national indicators may be useful in predicting general probability of bankruptcy, but will not be useful in cross-sectional sample to distinguish between failed and nonfailed firms.

However, as it has become common, the traditional approach of sample match is not always followed in failure prediction practice. A sample may contain unequal number of failed firms and nonfailed firms as the way it is in reality. Also, in many cases, a training sample contains observations over multiple years to obtain a sample that contains sufficient number of failed observations. In these cases, there are likely shifts of underlying economic environments and the impact of macro conditions on failure prediction becomes a factor that cannot be dismissed.

One perspective is to examine the effect of macro economic environment on prediction accuracy through the model stationarity. Eisenbeis (1977) was among the first to mention the time series problems in discriminant analysis, when discriminant analysis is applied to predict future events, or/ and when sample data are pooled across time periods. An empirical examination was later provided by Mensah (1984). Mensah studied the stationarity of bankruptcy prediction models by dividing an entire sample from 1972 to 1980 into four subperiods, depending on the particular state of macroeconomic environment (steady growth, recession, steady growth, and stagnation and recession). The results show that although the model based on the entire period can be deemed robust, it is inferior to the models estimated over single subperiod. Also, across the four subperiods, the parameters change substantially, suggesting the bankruptcy prediction models are fundamentally nonstationary.

The nonstationarity problem due to changes in macroeconomic conditions may be compared to the industry effect that has been well addressed. Industry effect becomes a problem when firms from industries are pooled together and when a model developed in one industry is used to predict firm failure in another. The macroeconomic effect issue is similar to industry effect problem, except that it is in a time series dimension, not cross sectional. Also, the underlying cause is due to changes in economic environment, not industry difference. Just as industry relative ratio takes out industry difference by placing companies from different industries on the same metric (see Platt and Platt (1990, 1991) for a rationale behind), the inclusion of macro variables may also remove the nonstationarity caused by the shifts of macroeconomic environment.

How much the inclusion of macro variables can add incrementally to the firm level information remains an empirical question. There is one subtle difference between industry effect and macro effect. For industry effect, as an example, a firm leveraged to certain level may not fail in one industry, but will fail in another. This industry difference is not factored in unless it is explicitly addressed, e.g. via the use of relative ratios or dummies. For the macro effect, firms experience the changes as the economy fluctuates and financial ratios capture them. The incremental information content of macroeconomic variables in this context appears harder to determine and is the main hypothesis we test in this study. Of course, a result of this test would also depend on the particular macro variables selected.

Relevant Macroeconomic Conditions

We consider specifically three aspects of macroeconomic condition as the potential variables to include in failure prediction, including economic growth, monetary condition, and inflation. This selection is based on the macro line of research on economy and business failure relationship. Among others, Altman (1971, 1983), Rose et al. (1982), Wadhwani (1986), Platt and Platt (1994), Melicher and Hearth (1988), and recently Liu (2004), have studied the influences of economic condition on business failures. The variables selected are among the most used in studies. A brief discussions and empirical results regarding these three macro conditions are as below.

Economic growth. Economic intuition suggests that economic growth is a fundamental factor as it is believed to have direct influence on a firm’s sales and earnings, and consequently a firm’s propensity to fail. Represented by GNP and aggregate corporate profits, economic growth has been generally found to be negatively associated with the aggregate business failures.

Monetary Condition. Money, or credit availability and its cost, is another factor supposed to have direct impact on marginal firms’ survival. “Regardless of how poorly a firm is performing, it seldom is motivated to declare bankruptcy as long as liquidity is sufficient or credit is available” (Altman, 1983). It is expected that the propensity to fail will be increased during periods of relatively tight credit conditions. Interest rate can be used to capture this monetary condition.

Inflation. The impact of price changes on business failures is less clear. Altman (1983) postulated that inflation, especially unanticipated price changes, may be inversely correlated with failures. On the other hand, Wadhwani (1986) and Liu (2004) found evidence that inflation leads to more business failures.

4.3 Data and Methodology

A sample of U.S. airline firms, under SIC code classification number 4512, was obtained from Mergent Online. This section of Mergent Online contains a total of 42 firms. A list of companies which experienced failure was first identified. In this study, the failed or bankrupt firms are defined as those which filed for bankruptcies protection (mostly under chapter 11) some point during 1990 to 2005. In addition, a few firms became inactive because they were bought by other firms. An examination of their financial ratios prior to purchase suggests that some of them are very financially stressed and then treated as failed firms. Two firms were bought when they appeared to be in very good shape financially. Those two firms are treated as nonfailed before they were bought. A total of 15 failed firms were identified using this procedure.

There are two options in the selection of nonfailed firms. One approach involves matching one failed firm with one nonfailed firm with similar size (asset or employee) in the same industry (Altman, 1968; Mensah, 1984). The other option uses all firms available in an original sample (Ohlson, 1980; Lennox, 1999). With this approach, total asset as a size variable can be introduced as an independent variable and the effect of size on bankruptcy can be investigated. This approach of no match is adopted here as we are interested in the effect of size on failure. Also, using all failed firms results in more observations in our sample.

For the failed firms, financial data one year prior to their failure is used. An analysis of failed firms indicates that all the 15 bankruptcies occurred during the period from 1996 through 2005. We choose year observations for nonfailed firms during the same period. Following literature (Ohlson, 1980; Izan, 1984; Richardson, et al., 1998; Hunter and Isachenkova, 2006), for each nonfailed firm, a year observation is selected randomly[9] during the peirod1996 to 2005. A distribution of firm year observations for failed and nonfailed firms is shown in figure 4.1. Given this distribution of firm data, the macroeconomic conditions from 1995 to 2005 are of particular interest to us.

Variables Selection

For each firm in the airline industry, Mergent Online provides firm financial ratios in four groups, including profitability ratios, liquidity indicators, debt management, and asset management. As in many bankruptcy prediction studies, missing values present a serious problem in our sample. All ratios are not available for each firm. Moreover, even when a financial ratio is available for a firm, values can be missing for certain years. This missing value problem limits the choice of variables. Fortunately, there is at least one financial ratio in each group that provides complete observations, or only requires a little data imputation. These ratios are operating margin, quick ratio, total debt to equity ratio, and interest coverage[10]. Beside financial ratios, total asset is also used to represent firm size.

Macroeconomic variables are selected based on the line of literatures that deal with aggregate business failure causality. Three conditions are considered, economic growth, interest rate, and inflation. Particularly, these conditions are represented by the following indicators, including gross domestic product (GDP) growth rate, 3 month

[9] It is found that the random sampling procedure can result in variations in the following estimation results and further study of this issue is needed. We suggest that the results reported in this study be used with caution.

[10] Operating margin is operating income divided by revenue. Quick ratio is current assets less inventories divided by current liabilities. Total debt to equity is total debt divided by total equity. Interest coverage is income before tax and interest divided by interest.

treasury bill rate (level and difference), consumer price index (CPI) (level and difference), resulting in a total of five potential macro variables. We expect a negative sign for GDP growth, and a positive sign for Treasury bill rate as it is supposed that there will be less bankruptcies during economic boom while high interest rate will lead to more bankruptcies given the importance of credit to marginal firms. The sign on inflation is less clear given the lack of well established theory and the inconsistency in empirical studies.

Statistical Models

The logit model (Ohlson, 1980; Maddala, 1988) is chosen to conduct the failure prediction analysis in this study. Although there are alternative discriminant analysis models, the logit model is selected because it is easier to test parameter significance and parameter stability. In the logit model, for an observed binary variable y_i (business failure in this case), there is a unobserved "latent" variables y^*, assumed as

$$Y_i^* = \beta' X_i + u_i \tag{4.1}$$

where X_i is the set of independent variables, explaining the happening of business failures in this case.

$$y_i = 1 \text{ if } Y_i^* \geq 0 \tag{4.2}$$

$$y_t = 0 \quad \text{otherwise.}$$

Given the above relationship, the probability of observing $y_i = 1$ and $y_i = 0$ is

$P_i = \Pr ob(y_i = 1) = \Pr ob(u_i > -(\beta' X_i)) = 1 - F[-(\beta' X_i)]$ (4.3), and

$$P_i = \Pr ob(y_i = 0) = \Pr ob(u_i < -(\beta' X_i)) = F[-(\beta' X_i)] \qquad (4.4)$$

where F is the cumulative distribution function for u_i.

Consequently, the likelihood function can be written as

$$l(\beta) = \sum_{i=1}^{n} y_i \cdot \log(1 - F(-\beta' X_i)) + (1 - y_i) \cdot \log(F(-\beta' X_i)) \qquad (4.5)$$

As in other binary models, the interpretation of coefficients in logit model is not straightforward as in multiple regression models. Instead, the marginal effect on probability dependent variable is given by

$$\frac{\partial E(y_i \mid X_i, \beta)}{\partial x_{ij}} = f(-\beta' X_i) \cdot \beta_j \qquad (4.6)$$

where β_j indicates the j_{th} parameter in parameter vector β.

Initial Estimation and Reduction of Variables

The selection of independent variables in the model follows a two step process. In the first step, the firm level variables are determined without consideration of macro variables. Total asset is first selected, to capture the effect of firm size on firm failures. The inclusion of firm financial ratio variables has been determined based on three factors. First, the financial ratio variables selected had complete or very few missing observations. Second, to avoid multicollinearity, there was a low level of correlation between the financial ratios selected. Only one financial ratio was chosen from each of the four groups from profitability to asset management. Third, the variable selected demonstrated discriminating power between failed and nonfailed group of firms. The above criteria resulted in three candidate variables being selected, including operating margin, quick ratio, and interest coverage. Total debt to equity ratio was dropped because it was not significantly different between failed and nonfailed firms and turned out insignificant in the estimated model.

In the second step, five candidate macro variables are added to the above firm level variables one at a time. Logit estimation results show that only Treasury bill rate difference turns out significant. This result echoes the finding in Chapter III that business failures are partially influenced by interest rate.

4.4 Estimation Results and Model Validation

The above two specifications, the model using only firm level variables and the model using both firm and macro variables, are estimated in logit and the results are presented in table 4.1. In the first model, the total asset coefficient, representing size effect, is negative, but not statistically significant, indicating size effect may not be a big factor in determining bankruptcy tendency in airline industry. Operating margin and quick ratio, representing profitability and liquidity respectively, are both negative as expected. Operating margin is highly significant at 1 percent while quick ratio is also significant at 15 percent level. Quick ratio appears a more influential impact on bankruptcy with an elasticity of 4.61 than operating margin (0.51). The coefficient of interest coverage is positive and significant at 10 percent level, but the elasticity associated with interest rate is just 0.11. The small elasticity of this variable seems to suggest that interest coverage is not critical factor in airline industry.

The estimation result for the second model is presented in the lower half of table 4.1. The second model is augmented with the only statistically significant macro variable, the change of interest rate. Under this specification, the total asset coefficient remains negative but turns significant; quick ratio turns out to be more influential and significant at 10 percent. Overall, all the four micro parameters are close to those in the first model. The estimated macro variable, interest rate fluctuation, turns out to be positive and significant at 10 percent level. By this parameter, an increase in interest rate will increase a firm's tendency to fail.

In addition, the overall fit of the model is improved with the addition of this macro variable. McFadden R-squared, the analog to the R-squared measure in linear regression models, increases from 0.67 to 0.73.

Chow Prediction Test

Following Platt and Platt (1991) in the study of industry-relative ratios, 'Chow prediction test' is conducted to test the stability of estimated coefficients. The purpose of applying this test here is to compare the models with and without macro variables, and see if the parameter stability has improved with the inclusion of macro variable.

Chow test requires the whole sample be divided into two sub samples, with observations n_1 and n_2 respectively. With $n_2 > 1$, the F -test is given as

$$F = \frac{(RSS - RSS_1)/n_2}{RSS_1/(n_1 - k - 1)}$$

where RSS is the residual sum of squares from the estimation of all observations and RSS_1 is the residual sum of squares from the sub sample of n_1 observations, k is the number of parameters in equation. This test has an F distribution with degree of freedom n_2 and $n_1 - k - 1$.

The observations in the sample are first ordered by time, i.e. the year in which the financial ratios of failed and nonfailed firms are observed. Then, the first 29 observations (about 80 percent) are selected to be in sub sample 1, covering a period from 1996 to 2003; the remaining 8 observations are left to sub sample 2, covering years 2004 and 2005. Given this break point, the chow test on the model with firm level variables gives a statistic of 2.95, with $p = 0.019$, rejecting the null hypothesis that the regression parameters are stable. For the model with macro variables, the test statistic is 0.215, $p = 0.985$, indicating the null cannot be rejected. By this 'Chow prediction test', the inclusion of macro variable in the prediction model may increase parameter stability.

Prediction Performance Comparison

We then compare the two competing models based on their prediction performance. Beside within sample prediction, greater emphasis is placed on out-of-sample prediction (Platt and Platt, 1990) and jackknife prediction. To evaluate a model's prediction performance using out-of-sample observations, one would need to use only part of the sample for training, and the remaining observations, either from the same or a later period, is reserved for prediction. The limited number of firms in single industry, especially failed firms, has limited further division of sample. We obtain out-of-sample observations by extending prediction horizon backward. That is, for each failed firm, the data two and three years prior to their failures are used as out-of-sample observations respectively; for nonfailed firms, the same thing is done. We then test the effectiveness of two competing models on their ability in predicting failed and nonfailed firms two and three years earlier. With this backward extension, we are able to show better how the two competing models perform in predicting failures in advance. This test seems to be more relevant and rigorous than those based on out-of-sample observation only one year prior to failure.

We further compare the two models' performance using the Jackknife method. By Jackknife method, or Lachenbruch (1967) method, successively one of the 37 observations is excluded while the remaining 36 observations are used to estimate the model and the resulting model is applied to predict the excluded observation. Jackknife method is a prediction test widely used in discriminant analysis.

For the above within sample, out-of-sample, and jackknife prediction tests, we choose four levels of probabilities, 0.2, 0.3, 0.4, 0.5, as the cutoff probabilities. The less than 0.5 cutoff values are chosen to reflect the relatively higher cost of misclassification for failed firms in reality. The prediction performances of the two competing models, based on four levels of cutoff probability, are presented in table 4.2, table 4.3, and table 4.4 respectively. The within sample prediction results are first presented in table 4.2. At the lower end cutoff level 0.2, the model using only firm ratio variables gives better prediction results than the one augmented with macro variable; but for cutoff levels from 0.3 to 0.5, the model with macro variable performs better or as well.

The out-of-sample prediction results are presented in table 4.3. In panel A, based on two years prior to failure observations, we observe again that at lower cutoff values

(0.2 and 0.3), the model with macro variable is inferior to the model using only financial ratios; yet it performs as well or better at higher cutoff levels (0.4 and 0.5). In panel B, as prediction horizon is extended backward one more year, the model augmented with macro variable shows better results, achieving higher overall prediction accuracy at all cutoff levels. Looking further, this accuracy gain is achieved for the prediction of both the failed firms and nonfailed firms. As can be expected, from panel A to panel B, at all cutoff levels, prediction accuracies drop as prediction horizon is extended from two to three years. For example, at the cutoff probability of 0.4, the ratio-based model predicts correctly 73 percent of all firms two years before failure; but at three years before failure, only 57 percent is correctly identified. This trend is true at the other cutoff probabilities.

For the jackknife test results in table 4.4, the model with macro variable predicts better or as well at the cutoff probabilities of 0.3, 0.4, and 0.5, but not at 0.2. A breakdown into failed and nonfailed predictions shows that the relative supremacy comes from its better prediction on failed firms.

Probability Forecast Evaluation

We further evaluate the prediction ability of two competing models using the probability score. The probability score, or the Brier score, was introduced by Brier (1950) in weather forecasting. Its two recent applications to economics include those by Bessler and Ruffley (2004) and Casillas-Olvera and Bessler (2006). The Brier score for evaluation of prediction is applicable where probabilistic forecasting is used. It is adopted in this study to provide an evaluation independent of cutoff levels. We are not aware of a previous use of this criterion in the literature of business failure prediction.

More detailed discussions can be found from Yates (1988), Bessler and Ruffley (2004) and Casillas-Olvera and Bessler (2006). From the above sources, the concept of probability score is summarized below. Let d be an actual outcome (e.g., business failure or financial distress in this study) index where:

$d = 1$, if the event occurs

$d = 0$, if the event does not occur

The Brier score (1950), or the probability score, is then defined, for a single forecast case, as:

$$PS(p, d) = (p - d)^2 \tag{4.7}$$

where, p is the forecast probability that the event occurs. The probabilistic forecasting would be perfect with PS reaching a minimum value of 0 ($p = d = 1$, or $p = d = 0$); the forecasting is worst with PS reaching a maximum value of 1 ($p = 0$, $d = 1$; or $p = 1$, $d = 0$).

For multiple occasions indexed by $i = 1,..., N$, the mean of PS is given by

$$\overline{PS}(P, D) = (1/N) \cdot \sum_{i=1}^{N} (p_i - d_i)^2 \tag{4.8}$$

For the prediction results in this study, the corresponding Brier scores are presented in table 4.5. The first row of the table gives the Brier score for within sample prediction. For both failed and nonfailed firms, the model augmented with macro variable predicts better than the model using only firm level information, evidenced by its lower probability scores on an overall and breakdown (failed and nonfailed) basis. The scores for out-of-sample prediction results are given in the second and third row of the table. Between the two competing models, the model augmented with macro variable obtains higher score (indicating worse performance) on overall prediction. If we break this down, 2 years prior to failure, the model with macro variable does not do so bad on failed firms (0.346 compared with 0.344), but it is much worse on the prediction of nonfailed firms(0.151 vs. 0.131). For the case of 3 years prior to failure, the pattern reverses: compared to the model using firm information, the model with macro variable predict as well on nonfailed firms, but worse on failed firms. Finally, the fourth row presents the probability score for the jackknife prediction. The model with macro variable predicts worse on nonfailed firms (0.175 vs. 0.161), but much better on failed firms (0.133 vs. 0.170), maintaining a lower score (0.158 vs. 0.165) overall.

Probability score enables an evaluation not dependent on the choice of particular cutoff probabilities, but the results still remain divided between out-of-sample prediction and jackknife prediction. Since out-of-sample prediction is sample specific, the jackknife prediction is more reasonable a test on future prediction performance (Huberty, 1994). By this measure, the model augmented macro variable gives better prediction and should be preferred to the model using only firm level financial information.

The Brier score can be decomposed into various components for further analysis (Sanders, 1963; Murphy, 1972, 1973; Yates, 1988). We show below the decomposition by Yates (1988) in which the covariance between the forecast probability (P) and the actual outcome (D) is emphasized. Yates' decomposition, also called 'covariance decomposition', is given as:

$$\overline{PS}(P,D) = Variance(D) + Bias^2 + Scatter + MinimumVariance(P) - 2 \times Covariance(P,D) \quad (4.9)$$

$Variance(D)$ is the component completely exogenous to the forecaster. The other four components are under the forecaster's control and should be minimized as a whole to achieve a lower probability score. In particular, $Bias$ quantifies the overall miscalibration, i.e. how much the mean forecast probability $\overline{p}$ is too high or too low compared to the actual probability $\overline{d}$. $Scatter$ indicates the noise level contained in the forecast probability. $MinimumVariance(P)$ reflects the overall variance in the forecast probability P when there is no scatter about the conditional means of p_1 and p_0 (the forecast probabilities for occasions that do occur and those do not occur respectively). In contrast to $Scatter$, $Covariance(P,D)$ measures the responses of the forecasting to information related to events' occurrence and is critical to the forecasting problem (Yates, 1988).

A Yates' decomposition for the jackknife prediction of the two competing models is presented in table 4.6. Except that $Variance(D)$ is the component identical between two models, $MinimumVariance(P)$, $Scatter$, and $Bias^2$ are all greater for the model with macro variable. Especially, the $Bias$ for two models (0.067 vs. 0.036) indicate that both models tend to overpredict the probability of failures, and the inclusion of macro variable increases this miscalibration. However, shown by the greater

$Co\,\mathrm{var}\,iance(P, D)$, the model with macro variable appears to be better in incorporating information related to the occurrence of business failures and this leads to a better overall prediction.

4.5 Concluding Remarks

The concept of including macro variables in business failure prediction is intuitively appealing, but systematic study of this concept is limited. Several issues, including its rationale, comparative evaluation of its impact on prediction accuracy, and the choice of particular macro variables, have not been sufficiently covered in literature. In this study, we examine the above issues by looking at the firm failure prediction of the U.S. airline industry over 1995 to 2005, using data from Mergent Online.

Based on logit model as the statistical method, we start with an initial set of macroeconomic variables based on empirical studies dealing with economy-failure relationship; and select the macroeconomic variable(s) to include based on parameter significance. Among the candidate macroeconomic variables (levels and differences), interest rate difference turns out to be the one significant and is incorporated in the failure prediction model. This result is probably due to the comparatively high leverage featured in the airline industry.

We found that the prediction model augmented with macroeconomic variable (change of interest rate) shows greater parameter stability and better within sample prediction performance. Across different cutoff probabilities, the out-of-sample and jackknife prediction results are somewhat mixed between the macro augmented model and the one using firm financial ratios, with the former showing advantage at higher cutoff probabilities.

Further, we introduce probability score, or the Brier score, to provide an evaluation of the two competing models independent of cutoff probabilities. The result of probability score indicates the model containing macro variable as worse in out-of-sample prediction, but superior in jackknife prediction. A decomposition of probability score based on jackknife prediction suggests that the model with macro variable has a better response to information related to the occurrence of firm failures.

The findings in this study are not conclusive. Further research may rely on a richer set of data, e.g., a sample of larger size or an extension to other industries. As it is intended, the findings in this study should be viewed as industry specific. Different industries may not respond to the macroeconomic conditions in the same way. That would require different sets of macro variables, and possibly the effect of the macro variables on prediction accuracy will be not the same.

CHAPTER V

CONCLUSION

This dissertation investigates three issues on the causality and prediction of business failure. Specifically, the three issues include: a nonlinear model for mathematical programming based discriminant analysis, the relationship between aggregate business failures and macroeconomic conditions, and the use of macroeconomic conditions as independent variables in business failure prediction model.

In Chapter II, we study a nonlinear model for mathematical programming based discriminant analysis. Since mathematical programming was introduced into discriminant analysis in the early 1980s, the linear and quadratic forms of functions have been the dominant forms of functions used for classification. We investigate here the potential of a nonlinear type of classification function for discriminant analysis. Particularly, we propose a more generalized nonlinear model that allows for flexible degrees of nonlinearity and attempts to solve the resulting nonlinear problem using robust global optimizer genetic algorithm. Using a data set on Canadian farm loan and another on Japanese banking, the proposed model is evaluated against the linear and quadratic model under the Minimize Sum of Deviation and the Mixed Integer Programming formulations. The results show that across both data sets, each of the three models is the best in certain cases, but overall, the proposed nonlinear model appears to be the best. On the other hand, the fact that the nonlinear model does not perform best in all cases suggests that a more robust solver, based on genetic algorithm or other global optimizers, would be indispensable for further evaluation of this model.

In Chapter III, we investigate the causal relationship between aggregate business failures and macro economic variables. Based on quarterly US data from 1980 to 2004, aggregate business failures, aggregate corporate profits, interest rate, inflation, and S&P 500 are studied in an approach that combines structural VAR and directed acyclic graph. Specifically, DAG is used to provide for VAR a contemporaneous causal structure not available from theory; the VAR estimation results are then summarized using impulse response function and forecast error variance decomposition. The results show that aggregate business failures are influenced by interest rate, but it has been more exogenous than previously found elsewhere: contemporaneously, there is a causal flow from aggregate business failures to interest rate; in long run, business failures impact corporate profits and S&P500 while it is not impacted by the other variables except interest rates. The role regarding interest rate lends support to existing results and suggests that interest rate may be used as an instrument to control the level of aggregate business failures. The exogeneity of aggregate business failures, however, is surprising. Better understanding of the causes of business failures may be obtained by studying business failures liabilities and establishing its relation to aggregate business failures.

In Chapter IV, we study the use of macroeconomic conditions as independent variables in business failure prediction model. The incremental information content, parameter stability, and the choice of particular variables are of particular interest in this study. Based on logit model as the statistical procedure, the case of U.S. airline industry over 1995 to 2005 is investigated. We start with an initial set of macroeconomic variables based on empirical studies dealing with economy-failure relationship; and select the macroeconomic variable(s) to include based on parameter significance. Among the candidate macroeconomic variables (levels and differences), interest rate difference turns out to be the one significant and is incorporated in the failure prediction model. We found that the prediction model augmented with macroeconomic variable (change of interest rate) shows greater parameter stability and better within sample prediction performance. In terms of prediction, the relative performances of the two models vary across different cut-off values. We further introduce probability score, or the Brier score, to provide an evaluation of the two competing models independent of cutoff probabilities. The result of the probability score indicates the model containing macro variable as worse in out-of-sample prediction, but better in jackknife prediction. A decomposition of probability score based on jackknife prediction reveals that the model with macro variable has a better response to information related to the occurrence of firm failures. Further research is needed in this area to consider firm failures involving more industries and a wider scope of macroeconomic variables.

REFERENCES

Altman, E. (1968) Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance*, **23**, 589-609.

Altman, E. (1971) *Corporate bankruptcy in America*, Lexington Books, Lexington, MA.

Altman, E. (1983) Why businesses fail, *Journal of Business Strategy*, **3**, 15-21.

Altman, E. and Izan, H. (1984) Identifying corporate distress in Australia: An industry relative analysis, Working Paper, New York University.

Awokuse, T.O. and Bessler, D. A. (2003) Vector autoregressions, policy analysis, and directed acyclic graphs: An application to the US Economy, *Journal of Applied Economics*, **6**, 1-24.

Bajgier, S.M. and Hill, A.V. (1982) An experimental comparison of statistical and linear programming approaches to the discriminant problem, *Decision Sciences*, **13**, 604-18.

Banks, W. J. and Prakash, L. A. (1994) On the performance of linear programming heuristics applied on a quadratic transformation in the classification problem, *European Journal of Operational Research*, **74**, 23-8.

Beaver, W.H. (1966) Financial ratios as predictors of failure, supplement to the *Journal of Accounting Research*, **4**, 71-111.

Bernanke, B. (1981) Bankruptcy, liquidity, and recession, *The American Economic Review*, **71**, 155- 59.

Bernanke, B. (1986) Alternative explanations of the money-income correlation, *Carnegie-Rochester Conference Series on Public Policy*, **25**, 49-100.

Bessler, D.A. and Ruffley, R. (2004) Prequential analysis of stock market returns, *Applied Economics*, **36**, 399-412.

Bessler, D.A. and Yang, J. (2003) The structure of interdependence in international stock markets, *Journal of International Money and Finance*, **22**, 261-87.

Bhandari, D., Murthy, C.A. and Sankar, K. P. (1996) Genetic algorithm with elitist model and its convergence, *International Journal of Pattern Recognition and Artificial Intelligence*, **10**, 731-47.

Brier, G. W. (1950) Verification of forecast expressed in terms of probability, *Monthly Weather Review*, **78**, 1-3.

Casillas-Olvera, G. and Bessler, D.A. (2006) Probability forecasting and central bank accountability, *Journal of Policy Modeling*, **28**, 223-34.

Chava, S. and Jarrow, R. (2004) Bankruptcy prediction with industry effects, *Review of Finance*, **8**, 537-69.

Demiralp, S. and Hoover, K. D. (2003) Searching for the causal structure of a vector autoregression, *Oxford Bulletin of Economics and Statistics*, **65**, 745-67.

Dimitras, A.I., Zanakis, S.H. and Zopounidis, C. (1996) A survey of business failures with an emphasis on prediction methods and industrial applications, *European Journal of Operational Research*, **90**, 487-513.

Dorsey, R.E. and Mayer, W.J. (1995) Genetic algorithms for estimation problems with multiple optima, nondifferentiability, and other irregular features, *Journal of Business & Economic Statistics*, **13**, 53-66.

Duffie, D. and Wang K. (2004) Multi-period corporate failure prediction with stochastic covariates, Working Paper, Stanford University.

Eisenbeis, R. (1977) Pitfalls in the application of discriminant analysis in business, finance, and economics, *Journal of Finance*, **32**, 875-900.

Enders, W. (2004) *Applied econometric time series* (2nd edition), John Wiley, New York.

Fisher, R.A. (1936) The use of multiple measurements in taxonomic problems, *Annals of Eugenics*, **7**, 179-88.

Freed, N. and Glover, F. (1981a) A linear programming approach to the discriminant problem, *Decision Science*, **12**, 68-74.

Freed, N. and Glover, F. (1981b) Simple but powerful goal programming models for discriminant problems, *European Journal of Operational Research*, **7**, 44-60.

Freed, N. and Glover, F. (1986) Evaluating alternative linear programming models to solve the two-group discriminant problem, *Decision Sciences*, **17**, 151-162.

Goldberg, D. E. (1989) *Genetic algorithms in search, optimization & machine learning*, Addsion-Wesley Publishing Company, Inc., Reading, MA.

Grefenstette, J.J. (1990) *A user's guide to genesis version 5. 0,* Technical report, Navy Center for Applied Research in Artificial Intelligence, Washington, DC.

Hand, D.J. (1981) *Discrimination and classification*, Wiley, New York.

Hansen, H. and Juselius, K. (1995) CATS in RATS: *Cointegration analysis of time series*, Estima, Evanston, IL.

Holland, J. H. (1962a) Concerning efficient adaptive systems. in Yovits M. C., Jacobi G. T., and Goldstein G. D. (Eds.), *Self-organizing systems,* Spartan Books, Washington, DC, pp. 215-30.

Holland, J. H. (1962b) Information processing in adaptive systems, information processing in the nervous system, *Proceedings of the International Union of Physiological Sciences*, **3**, 330-39.

Holland, J. H. (1962c) Outline for a logical theory of adaptive systems, *Journal of The Association for Computing Machinery,* **3**, 297-314.

Holland, J. H. (1975) *Adaptation in natural and artificial systems*, The University of Michigan Press, Ann Arbor.

Holland, J. H. (1976) *Adaptation*, in: Rosen, R. , Snell, F. M. (Eds.), *Progress in theoretical biology*, Vol. 4, Academic Press, New York, pp. 263-93.

Holland, J. H. (1980) Adaptive algorithms for discovering and using general patterns in growing knowledge-bases, *International Journal of Policy Analysis and Information Systems*, **4**, 217-40.

Holland, J. H. (1992) *Adaptation in natural and artificial systems*, MIT Press, Cambridge, MA.

Huberty, C. J. (1994) *Applied discriminant analysis*, Wiley, New York.

Hunter, J. and Isachenkova, N. (2006) Aggregate economy risk and company failure: an examination of UK quoted firms, Working Paper, Research Papers in Economics.

Izan, H. (1984) Corporate distress in Australia, *Journal of Banking and Finance*, **8**, 303-20.

Jones, F. (1987) Current techniques in bankruptcy prediction, *Journal of Accounting Literature*, **6**, 131-64.

Kane, D., Richardson, F. and Graybeal, P. (1996) Recession-induced stress and the prediction of corporate failure, *Contemporary Accounting Research*, **13**, 631-50.

Lachenbruch, P. (1967) An almost unbiased method of obtaining confidence intervals for the probability of misclassification in discriminant analysis, *Biometrics*, **23**, 639-45.

Lennox, C. (1999) Identifying failing companies: A re-evaluation of the logit, probit and DA approaches, *Journal of Economics and Business*, **51**, 347-64.

Liu, J. (2004) Macroeconomic determinants of corporate failures: evidence from the UK, *Applied Economics*, **36**, 939-45.

Maddala, G.S. (1988) *Introduction to Econometrics*, Macmillan, New York.

McCarl, B. A. and Spreen, T. H. (2003) *Applied mathematical programming using algebraic systems*, Course Materials: AGEC 641, Texas A&M University, College Station.

Melicher R.W. and Hearth, D. (1988) A time series analysis of aggregate business failure activity and credit conditions, *Journal of Economics and Business*, **40**, 319-33.

Mensah, Y. (1984) An examination of the stationarity of multivariate bankruptcy prediction models: a methodological study, *Journal of Accounting Research*, **22**, 380-95.

Mergent Online, www.mergentonline.com, Accessed: July 2006.

Moore, G.H. (1950) Statistical indicators of cyclical revivals and recessions, *Occasional paper*, **31**, National Bureau of Economic Research.

Murphy, A.H. (1972) Scalar and vector partitions of the probability score: part II. Two-state situation, *Journal of Applied Meteorology*, **11**, 1183-92.

Murphy, A.H. (1973) A new vector partition of the probability score, *Journal of Applied Meteorology*, **12**, 595-600.

Ohlson, J. (1980) Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research*, **18**, 109-31.

Ostermark, R. (1999) Solving irregular econometric and mathematical optimization problems with a genetic hybrid algorithms, *Computational Economics*, **13**, 103-15.

Pearl, J. (1986) Fusion, propagation, and structuring in belief networks, *Artificial Intelligence*, **29**, 241-88.

Platt, H. and Platt, M. (1990) Development of a class of stable predictive variables: the case of bankruptcy prediction, *Journal of Business Finance and Accounting*, **17**, 31-51.

Platt, H and Platt, M. (1991) A note on the use of industry-relative ratios in bankruptcy prediction, *Journal of Banking and Finance*, **15**, 1183-94.

Platt, H. and Platt, M. (1994) Business cycle effects on state corporate failure rates, *Journal of Economics and Business*, **46**, 113-27.

Richardson, F. M., Kane G.D. and Lobingier P. (1998) The impact of recession on the prediction of corporate failure, *Journal of Business Finance and Accounting*, **25**, 167-86.

Rose, P.S., Andrews W.T. and Giroux G.A. (1982) Predicting business failure: A macroeconomic perspective, *Journal of Accounting, Auditing, & Finance*, **6**, 20-31.

Sanders, F. (1963) On subjective probability forecasting, *Journal of Meteorology*, **2**, 191-201.

Scheines, R., Spirtes P., Glymour C. and Meek C. (1994) *TETRAD II: User's manual and software*, Lawrence Erlbaum Associates, Inc., Mahwah, NJ.

Shumway, T. (2001) Forecasting bankruptcy more accurately: a simple hazard model, *Journal of Business*, **74**, 101-24.

Silva, A.P.D. and Stam, A. (1994) Second order mathematical programming formulations for discriminant analysis, *European Journal of Operational Research*, **72**, 4-22.

Simpson, P.B. and Anderson, P.S. (1957) Liabilities of business failures as a business indicator, *Review of Economics and Statistics*, **39**, 193-99.

Sims, C. (1980) Macroeconomics and reality, *Econometrica*, **48**, 1-48.

Sims, C. (1986) Are forecasting models usable for policy analysis? *Quarterly Review of Federal Reserve Bank of Minneapolis*, **10**, 2-16.

Spirtes, P., Glymour C. and Scheines R. (2000) *Causation, prediction, and search,* second edition, MIT Press, Cambridge, MA.

Sueyoshi, T. (2001) Theory and methodology: extended DEA-discriminant analysis, *European Journal of Operational Research*, **131**, 324-51.

Swanson, N.R. and Granger, C.W.J. (1997) Impulse response functions based on a causal approach to residual orthogonalization in vector autoregression, *Journal of the American Statistical Association*, **92**, 357-67.

Thomas, L.C. (2000) A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers, *International Journal of Forecasting*, **16**, 149-72.

Tirapat, S. and Nittayagasetwat, A. (1999) An investigation of Thai listed firms' financial distress using macro and micro variables, *Multinational Finance Journal*, **3**, 103– 25.

Verma, T. and Pearl, J. (1988) Causal networks: semantics and expressiveness, *Proceedings of the 4th Workshop on Uncentainty in Artificial Intelligence* (Mountain View, California), pp.352-359. Reprinted in R. Shachter, T.S.Levitt, and L.N. Kanal (Editors), *Uncertainty in artificial intelligence*, 4:69-76, Elsevier, Amsterdam.

Wadhwani, S.B. (1986) Inflation, bankruptcy, default premia, and the sock market, *The Economic Journal*, **96**, 120-38.

Yates, F. (1988) Analyzing the accuracy of probability judgements for multiple events: an extension of the covariance decomposition, *Organizational Behavior and Human Decision*, **41**, 281-99.

Ziari, H. A., Leatham, D. J. and Turvey, C.G. (1995) Application of mathematical programming techniques in credit scoring of agricultural loans, *Agricultural Financial Review*, **55**, 74-88.

Zmijewski, M. E. (1984) Methodological issues related to the estimation of financial distress prediction models, **22**, 59- 82.

APPENDIX A

TABLES

Table 2.1. Classification results using Canadian credit scoring data

Cases	Models	Objective function value	Total correct classification	Correct classification for current loans	Correct classification for noncurrent loans
Within Sample (sample size is 1199)					
	MSD	27.94	0.523	0.312	0.644
	MSD-QD	58.05	0.578	0.417	0.670
	MSD-NL	13.47	0.577	0.401	0.678
Case 1	MIP	387	0.677	0.335	0.873
	MIP-QD	432	0.640	0.025	0.991
	MIP-NL	435	0.637	0.002	1.000
Case 2	MIP	435	0.637	0.002	1.000
	MIP-QD	433	0.639	0.007	1.000
	MIP-NL	432	0.640	0.009	1.000
Case 3	MIP	625	0.525	0.872	0.328
	MIP-QD	632	0.520	0.869	0.321
	MIP-NL	615	0.598	0.695	0.543

Table 2.1. Continued

Cases	Models	Objective function value	Total correct classification	Correct classification for current loans	Correct classification for noncurrent loans
Out-of-sample (sample size is 800)					
	MSD	18.79	0.528	0.327	0.660
	MSD-QD	78.29	0.591	0.472	0.670
	MSD-NL	12.08	0.565	0.396	0.676
Case 1	MIP	262	0.673	0.437	0.828
	MIP-QD	324	0.595	0.003	0.985
	MIP-NL	318	0.603	0.003	0.998
Case 2	MIP	319	0.603	0.003	0.998
	MIP-QD	326	0.598	0.000	0.992
	MIP-NL	322	0.601	0.006	0.994
Case 3	MIP	414	0.515	0.918	0.249
	MIP-QD	416	0.515	0.912	0.253
	MIP-NL	414	0.580	0.755	0.465

Notes:
1. MSD = minimize sum of the deviations, MIP = mixed integer model, LN = linear, QD = quadratic, NL = nonlinear. For example, MSD-LN = MSD formulation based on linear classification function.
2. Three cases are reported for MIP evaluation. In case 1, 2, and 3, the misclassification costs associated with current and noncurrent loans are 1:1, 1:2, and 2:1 respectively.
3. The classification results are reported in ratios.

Table 2.2. Classification results using Japanese banking data

Cases	Models	Objective function value	Total correct classification	Correct classification for top banks	Correct classification for bottom banks
		Within Sample (sample size is 50)			
	MSD	2.55	0.92	0.92	0.92
	MSD-QD	395.81	0.74	0.76	0.72
	MSD-NL	0.45	0.92	0.92	0.92
Case 1	MIP	13	0.74	0.80	0.68
	MIP-QD	12	0.76	0.72	0.80
	MIP-NL	4	0.92	0.92	0.92
Case 2	MIP	18	0.74	0.68	0.80
	MIP-QD	22	0.68	0.60	0.76
	MIP-NL	14	0.76	0.60	0.92
Case 3	MIP	18	0.74	0.80	0.68
	MIP-QD	18	0.74	0.80	0.68
	MIP-NL	20	0.62	0.96	0.28
		Out-of-sample (sample size is 50)			
	MSD	18.51	0.72	0.80	0.64
	MSD-QD	731.17	0.80	0.88	0.72
	MSD-NL	5.31	0.74	0.76	0.72
Case 1	MIP	25	0.50	0.60	0.40
	MIP-QD	21	0.58	0.48	0.68
	MIP-NL	24	0.52	1.00	0.04
Case 2	MIP	26	0.60	0.44	0.76
	MIP-QD	35	0.50	0.40	0.60
	MIP-NL	19	0.68	0.48	0.88
Case 3	MIP	36	0.50	0.56	0.44
	MIP-QD	36	0.50	0.56	0.44
	MIP-NL	24	0.58	0.88	0.28

Notes:
1. MSD = minimize sum of the deviations, MIP = mixed integer model, LN = linear, QD = quadratic, NL = nonlinear. For example, MSD-LN = MSD formulation based on linear classification function.
2. Three cases are reported for MIP evaluation. In case 1, 2, and 3, the misclassification costs associated with top and bottom banks are 1:1, 1:2, and 2:1 respectively.
3. Except the objective function value, the correct classification results are in ratios.

Table 2.3. Summary of results in tables 2.1 and 2.2

		Training Sample		Validation Sample		
		objective function	Classification performance	objective function	Classification performance	Sum
Table 2.1	Linear	6	7	9*	8	30
	Quadratic	5	8	3	6	22
	Nonlinear	7*	9*	7	9*	32*
Table 2.2	Linear	6	9	4	5	24
	Quadratic	6	7	5	8	26
	Nonlinear	7*	10*	8*	10*	35*

Notes:
1. The numbers given in this table are scores assigned to each model given their relative performance in table 2.1 and 2.2. For example, the upper left cell reports a number of 6 for linear model based on its relative performance in terms of objective function value across all cases of MSD and MIP formulations. The sum measure at the end of each row further summarizes a model's relative performance across both training sample and validation sample.
2. Linear, quadratic, and nonlinear mean linear model, quadratic model, and the proposed nonlinear model respectively.
3. * indicates the best relative performance among the three models.

Table 3.1. Augmented Dickey-Fuller test for nonstationarity of data

Series	Without trend	With trend
BANKB	-0.98	-3.46
CORPP	1.36	-1.37
INT	-1.48	-2.97
PPIACO	-0.10	-2.93
SP500	-0.47	-2.01

Notes:
1. Critical values for Augmented Dickey-Fuller test at 5 % level without and with trend are -2.89 and -3.46 respectively. Nonstationarity is rejected when calculated values are less than critical values.
2. BANKB = aggregate business bankruptcies
   CORPP = corporate profits
   INT = interest rate
   PPIACO = producer price index of all commodities
   SP500 = Stand & Poor's 500 Index of stock prices.

Table 3.2. Akaike and Schwarz loss criteria measures on lag 1 to 10 for VAR

Number of Lag	Akaike loss	Schwarz loss
1	45.062	45.853[a]
2	45.147	46.607
3	44.980[a]	47.117
4	45.059	47.882
5	45.174	48.691
6	45.114	49.335
7	45.031	49.965
8	45.278	50.934
9	45.417	51.806
10	45.500	52.631

[a] Denote the minimum value for the corresponding loss criterion. For each criterion, the lag with the minimum value indicates the desirable lag under that loss criterion.

Table 3.3. Trace test statistics for the studied variables

r	Without linear trend			With linear trend		
	T	C(5%)	C(10%)	T	C(5%)	C(10%)
=0	124.21	75.74	71.66	100.68	68.68	64.74
<=1	73.47	53.42	49.92	53.64	47.21	43.84
<=2	40.51	34.80	31.88	32.25	29.38	26.70
<=3	21.03	19.99	17.79	13.63	15.34	13.31
<=4	5.90	9.13	7.50	1.21	3.84	2.71

Note: The trace test indicates the number of cointegration vectors (r) for cases with and without constant. The critical values (C) at 5% and 10% levels are as given in Hansen and Juselius (1995). To determine the number of cointegration vectors, we start with top row and move from the left column of “with constant” to the right column of “without constant”. This process continues to next row until we meet the first “fail to reject” case, i.e., when the trace test statistic (T) is less than the critical value (C).

Table 3.4. Forecast error variance decomposition based on the contemporaneous structure as modeled in figure 3.1

Step	BANKB	CORPP	INT	PPIACO	SP500
BANKB					
0	100.00	0.00	0.00	0.00	0.00
1	97.98	0.36	0.61	0.87	0.18
2	97.45	0.35	0.46	1.09	0.65
5	95.36	0.52	2.48	0.89	0.75
10	89.74	0.79	7.92	0.92	0.63
15	85.38	1.19	11.99	0.89	0.54
20	81.04	1.92	15.37	1.16	0.50
CORPP					
0	0.00	100.00	0.00	0.00	0.00
1	0.00	98.30	0.04	1.14	0.52
2	0.52	92.09	2.11	3.83	1.45
5	2.94	66.18	11.26	12.30	7.33
10	8.75	44.62	22.28	13.29	11.06
15	13.89	36.04	29.66	10.17	10.25
20	17.28	31.27	34.84	7.68	8.93
INT					
0	5.09	0.00	84.65	10.26	0.00
1	4.55	0.01	75.72	15.54	4.18
2	3.97	0.01	71.90	15.76	8.36
5	3.50	0.03	71.56	14.23	10.69
10	3.18	0.07	65.58	21.43	9.75
15	2.95	0.42	62.05	25.59	8.99
20	2.74	0.70	60.26	27.34	8.97
PPIACO					
0	0.00	0.00	0.00	100.00	0.00
1	0.00	1.10	0.00	97.89	1.01
2	0.03	1.47	0.11	96.68	1.71
5	0.10	2.71	4.28	91.42	1.50
10	0.11	2.73	15.65	74.67	6.84
15	0.17	1.97	21.27	66.92	9.67
20	0.14	2.41	21.14	67.16	9.15

Table 3.4. Continued

Step	BANKB	CORPP	INT	PPIACO	SP500
SP500					
0	0.00	3.55	0.00	0.00	96.45
1	0.40	2.93	0.06	1.79	94.82
2	0.42	4.42	0.15	4.98	90.04
5	0.25	14.16	0.86	15.48	69.24
10	1.74	29.70	0.64	33.29	34.63
15	5.80	33.09	2.71	41.30	17.11
20	10.46	32.28	6.39	40.55	10.32

Note: Steps are in quarters. In each of the 5 sections, the decomposition results for each variable are shown at 7 selected steps from 0 (contemporaneous) to 20. For each step (in a row), the decompositions sum up to one hundred. Each component of the decompositions means the percentage of variance that is due to a variable itself or the other variables (shown in column 1 to 5). BANKB, CORPP, INT, PPIACO, and SP500 are as spelled out in table 3.1.

Table 4.1. Estimation results based on logit model

Variable	Without macro variable			
	Coefficient	z-Statistic	p-value	Elasticity at means
Constant	2.66	1.49	0.14	
Total Asset	-5.16E-11	-0.83	0.41	-0.20
Operating Margin	-0.31	-3.28	0.00	-0.51
Quick Ratio	-3.55	-1.47	0.14	-4.61
Interest Coverage	0.01	1.85	0.07	0.11
McFadden R-squared	0.67			
	With macro variable			
	Coefficient	z-Statistic	p-value	Elasticity at means
Constant	4.72	1.95	0.05	
Total Asset	-1.59E-10	-2.10	0.04	-0.64
Operating Margin	-0.42	-3.27	0.00	-0.73
Quick Ratio	-5.47	-1.67	0.10	-7.40
Interest Coverage	0.02	2.22	0.03	0.17
Interest Rate Change	1.60	1.69	0.09	0.20
McFadden R-squared	0.73			

Note: "Without macro variable" indicates the model using only firm level information; "With macro variable" indicates the model augmented with macroeconomic condition.

Table 4.2. Within sample prediction results

Cut off Probability		0.2	0.3	0.4	0.5
Without macro variable	Overall	0.92	0.89	0.86	0.89
	Failed firms	1.00	0.93	0.87	0.87
	Nonfailed firms	0.86	0.86	0.86	0.91
With macro variable	Overall	0.86	0.92	0.89	0.89
	Failed firms	0.93	0.93	0.87	0.87
	Nonfailed firms	0.82	0.91	0.91	0.91

Note: "Without macro variable" indicates the model using only firm level information; "With macro variable" indicates the model augmented with macroeconomic condition. Prediction results are reported in ratios of firms correctly classified.

Table 4.3. Out-of-sample prediction results

Panel A: Two years prior to failure sample

Cut off Probability		0.20	0.30	0.40	0.50
Without macro variable	Overall	0.81	0.76	0.73	0.68
	Failed firms	0.80	0.67	0.60	0.40
	Nonfailed firms	0.82	0.82	0.82	0.86
With macro variable	Overall	0.73	0.73	0.73	0.73
	Failed firms	0.67	0.60	0.60	0.60
	Nonfailed firms	0.77	0.82	0.82	0.82

Panel B: Three years prior to failure sample

Cut off Probability		0.20	0.30	0.40	0.50
Without macro variable	Overall	0.59	0.59	0.57	0.57
	Failed firms	0.53	0.53	0.47	0.40
	Nonfailed firms	0.64	0.64	0.64	0.68
With macro variable	Overall	0.62	0.65	0.62	0.57
	Failed firms	0.60	0.60	0.53	0.40
	Nonfailed firms	0.64	0.68	0.68	0.68

Note: “Without macro variable” indicates the model using only firm level information; “With macro variable” indicates the model augmented with macroeconomic condition. Prediction results are reported in ratios of firms correctly classified.

Table 4.4. Prediction results based on jackknife method

Cut off Probability		0.2	0.3	0.4	0.5
Without macro variable	Overall	0.78	0.81	0.81	0.81
	Failed firms	0.87	0.80	0.80	0.80
	Nonfailed firms	0.73	0.82	0.82	0.82
With macro variable	Overall	0.76	0.81	0.81	0.84
	Failed firms	0.87	0.87	0.87	0.87
	Nonfailed firms	0.68	0.77	0.77	0.82

Note: "Without macro variable" indicates the model using only firm level information; "With macro variable" indicates the model augmented with macroeconomic condition. Prediction results are reported in ratios of firms correctly classified.

Table 4.5. Evaluation results using probability score

	Without macro variable			With macro variable		
Cases	Overall	Failed firms	Nonfailed firms	Overall	Failed firms	Nonfailed firms
Within sample	0.076	0.092	0.065	0.058	0.087	0.039
2 years prior to failure	0.217	0.344	0.131	0.230	0.346	0.151
3 years prior to failure	0.372	0.489	0.293	0.380	0.507	0.293
Jackknife	0.165	0.170	0.161	0.158	0.133	0.175

Note: "Without macro variable" indicates the model using only firm level information; "With macro variable" indicates the model augmented with macroeconomic condition.

Table 4.6. Brier score decomposition for prediction results based on jackknife method

	Score	Var(D)	MinVar(P)	Scatter	$Bias^2$	Cov(P,D)
Without macro variable	0.165	0.241	0.066	0.109	0.001	0.126
With macro variable	0.158	0.241	0.079	0.110	0.005	0.138

Notes:
1. "Without macro variable" indicates the model using only firm level information; "With macro variable" indicates the model augmented with macroeconomic condition.
2. Score is the Brier score. A lower score indicates better performance. Var(D), MinVar(P), Scatter, $Bias^2$, and Cov(P,D) are the five components of the Brier score. The relationship between the Brier score and its five components is defined as: Score = Var(D) + MinVar(P)+Scatter+ $Bias^2$ -2xCov(P,D).

APPENDIX B

FIGURES

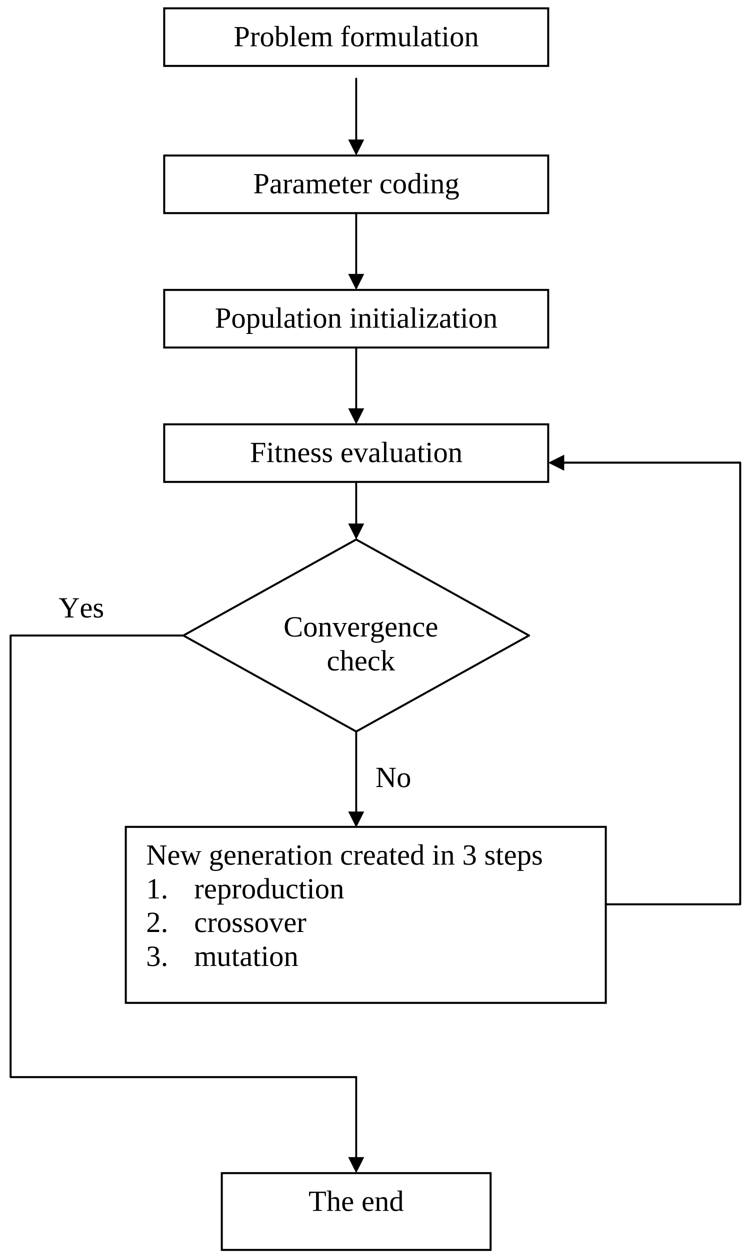

Figure 2.1. Typical flowchart of a genetic algorithm application

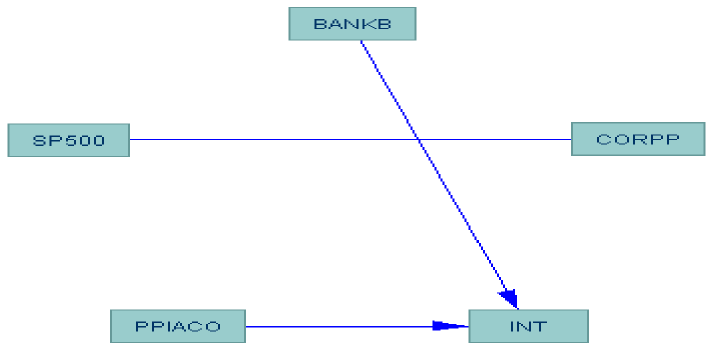

Figure 3.1. Directed graph patterns by PC algorithm at 20% and 30% significance level

Note: BANKB stands for aggregate business bankruptcies, CORPP for corporate profits, INT for interest rate, PPIACO for producer price index of all commodities, and SP500 for Stand & Poor's 500 Index of stock prices.

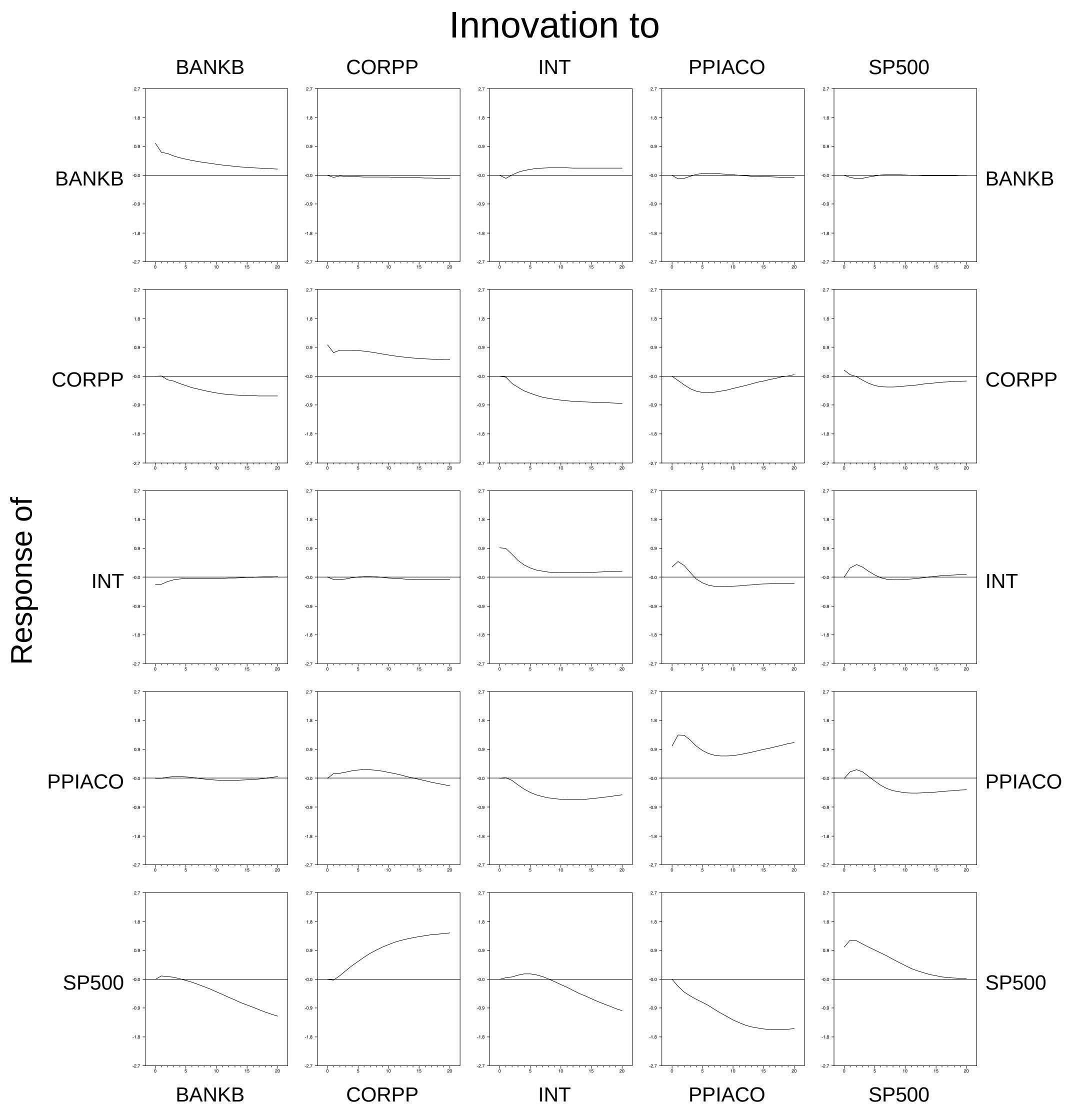

Figure 3.2. Impulse response functions based on the contemporaneous structure as modeled in figure 3.1

Note: Each of the 25 small graphs in the figure represents the response of a variable to itself or another variable. The responses of a variable to all variables (shown on top of the figure) are shown in a single row from column 1 to 5. Alternatively, the responses of all the five variables to the same shock can be read in a single column from row 1 to 5. For each response curve, the movement (response) of a variable has been normalized and over a period of 20 quarters.

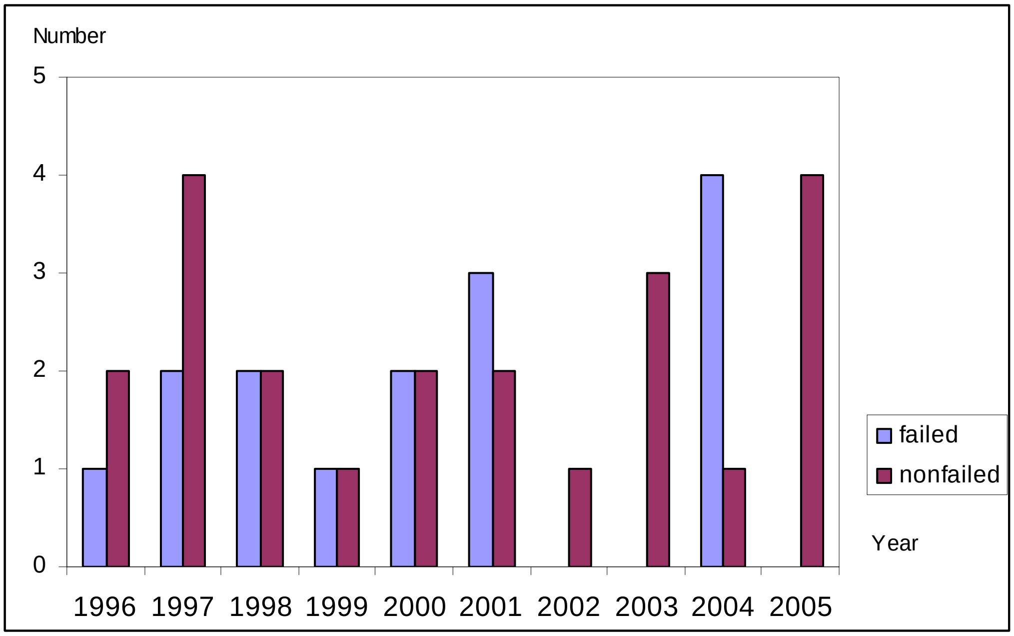

Figure 4.1. Distribution of firm year observations from 1996 to 2005

VITA

Jin Zhang was born in 1972, and was brought up in the eastern part of Sichuan Province, China. He received his B.S. and M.S. from Beijing University of Aeronautics and Astronautics, Beijing, China in Aircraft Design in 1994 and1997 respectively. Since 2000, he pursued a Ph.D. degree in the Department of Agricultural Economics, Texas A&M University, with an emphasis on finance and received his degree in 2006. He has published three papers in economics and finance journals, including *Applied Economics Letters*, *Journal of Transportation Research Forum*, *Annals of Economics and Finance*. He can be reached at the address: 28 YuHeXiang, WanZhouQu, ChongQing City, China, 404000.